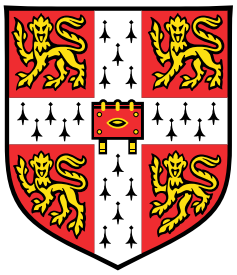
Perception, expectation and uncertainty in autism



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This dissertation is submitted for the degree of
Doctor of Philosophy

Robinson College

January 2019

I would like to dedicate this thesis to my wife, my parents and to all the participants who helped make this research possible.

Declaration

I hereby declare that except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other university. This dissertation is my own work and contains nothing which is the outcome of work done in collaboration with others, except as specified in the text and Acknowledgements. This dissertation does not exceed the prescribed word limit of 60,000 words.

Owen Edward Parsons
January 2019

Acknowledgements

I am incredibly grateful to a number of people who helped to support me during the writing of this thesis. I am particularly appreciative of Simon Baron-Cohen and Sara Baker for giving me the opportunity to come to Cambridge and for helping me during the application process. Simon, you have been a fantastic supervisor during my time in Cambridge. I am particularly grateful for the independence you allowed me, while always providing support and encouragement when needed. I would also like to thank the Medical Research Council who funded me throughout my PhD and made this work possible.

Thank you to Ezra Aydin, Richard Bethlehem, Varun Warrier for being wonderful office companions. I am thankful to Jan Freyberg, who not only acted as a good friend but also offered me a lot of advice in the early stages of my PhD, and Becky Kenny, for always making time for me when I had questions.

I am grateful to Alex Coles, Joe Palana and Charlotte Snelling for helping to collect pilot data for the behavioural tasks presented in this thesis. I would also like to thank Johanna Finnemann who I collaborated with to collect the psychometric data presented in this thesis. I am particularly thankful and appreciative of the generous support I received from Chris Ashwin, Rosa Hoekstra, Sarah Cassidy and Bhismadev Chakrabarti, all of whom allowed me to use their facilities during my data collection.

I had a number of fascinating and incredibly helpful conversations during my PhD and would like to thank Liz Pellicano, Rasmus Bruckner, Christopher Summerfield, Rebecca Lawson, Joost Haarsma, Johanna Finnemann and Cathy Manning. I also would not have been in this position were it not for a number of brilliant teachers during my time at school. In particular, I would like to thank Michael Mayell who was the first teacher to give me confidence in my abilities in maths and science.

My time in Cambridge wouldn't have been the same without a number of friends who provided support and a welcome distraction from work. I am also incredibly grateful to my wonderful parents, Barry and Pam, who have given me an enormous amount of support over the years. And finally, to my amazing wife Emma. Thank you for all the support and for knowing when to tell me to stop moaning and just get on with it, I couldn't have done it without you.

Abstract

It has been suggested that autistic individuals acquire and use statistical information about their external environment atypically. This thesis uses behavioural measures and self-report questionnaires to understand how autistic individuals extract predictive information from their environment, how this predictive information influences perception in autism and how these processes are associated with other clinical features of autism.

In chapter 1, I review the literature on perception, sensory issues, anxiety and learning in autism. In chapter 2, I discuss Bayesian models of perception and introduce a set of explanatory accounts that suggest autistic individuals have difficulty in utilising prior expectations during perception.

In chapter 3, I present an interrupted search paradigm and show that autistic individuals perform similarly to non-autistic controls on this task. In chapter 4, I demonstrate that autistic individuals did not significantly differ from non-autistic controls in the extent to which prior information guides attention during visual search. In chapter 5, I develop a novel modelling approach which further supports the initial findings from chapter 4. Taken together, chapters 3-5 provide a clear case of one aspect of perception in which prior information is used by autistic and non-autistic individuals in a similar manner.

In chapter 6, I present a serial reaction time task which tests whether autistic individuals are able to update predictive information flexibly. The results found that autistic individuals, relative to controls, showed an overall reduction in the extent to which they utilised prior information during the task, but this was not specific to conditions in which they were required to update information about the underlying statistical regularities in the task. In chapter 7, I use a visual statistical learning task to test whether autistic individuals are able to implicitly acquire predictive statistical information to the same extent as non-autistic controls. Importantly, I also examine whether autistic individuals are able to acquire information which is processed at higher-order perceptual levels rather than low-level features. The results suggest that autistic individuals show a slightly reduced effect of learning when compared to non-autistic controls, but this effect is not specific to high-level information.

In chapter 8, I present a number of different questionnaire measures for which differences are found between autistic and non-autistic individuals. In chapter 9, I evaluate the construct

of ‘intolerance of uncertainty’ and how it relates to other features of autism. In chapter 10, I show that ‘intolerance of uncertainty’ plays a mediating role in clinical features associated with autism, such as anxiety and sensory issues.

In chapter 11, I discuss the importance of these findings in relation to a number of different accounts of autism and suggest that the cognitive mechanisms involved in processing predictive information are key to understanding autism.

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Part I

Introduction

Chapter 1

Perception, sensory issues and learning in autism

Autism[1] affects approximately 1% of the population (Baird et al., 2006; Baron-Cohen et al., 2009b; Brugha et al., 2011). While autism has been traditionally defined by social deficits alongside unusually restrictive behaviours, the importance of atypical sensory processing has recently come to be recognised as a key aspect (Marco et al., 2011) and is now a diagnostic feature of the condition (DSM-5 American Psychiatric Association, 2013). Perceptual differences in autism have been widely reported in the academic literature (Dakin and Frith, 2005) and are thought to be linked to the severity of social difficulties experienced (Kern et al., 2007; Simmons et al., 2009). The underlying mechanism that drives the co-occurrence of social communication difficulties and perceptual atypicalities is yet to be fully understood. A number of different theories have offered explanatory accounts for some of the core features of autism, but these have tended to focus on certain aspects of the condition rather than providing broader explanations (Baron-Cohen, 2006; Frith and Happé, 1994; Happé and Frith, 2006; Mottron and Burack, 2001; Mottron et al., 2006).

1.1 Visual perception in autism

There are a number of perceptual tasks in which autistic individuals have been reported to outperform the typical population. Autistic individuals show higher than average abilities on behavioural paradigms such as the Embedded Figures Task, which measures the ability to

[1] I have tried to be mindful of the language used in this thesis to describe autism, following suggestions from the results of Kenny et al. (2016). I will primarily use disability-first terms to refer to the autistic participants who took part in the studies reported here. However, other terms may occasionally be used where deemed appropriate.

find basic shapes within more complex stimuli presentations (Jolliffe and Baron-Cohen, 1997; Shah and Frith, 1983, 1993), and visual search tasks (Joseph et al., 2009; O'riordan et al., 2001; Plaisted et al., 1998b), as well as showing a reduced susceptibility to visual illusions (Happé, 1996). Conversely, there are also a number of aspects of perception in which autistic individuals have showed lower levels of discrimination such as motion coherence (Milne et al., 2002, 2006) and form processing (Spencer and O'Brien, 2006; Tsermentseli et al., 2008). The existence of atypical visual perception in autism initially led to attempts to identify differences in low-level visual mechanisms (Scharre and Creedon, 1992). Milne et al. (2009) looked at visual acuity, stereoacuity, convergence, divergence, ocular motility, strabismus and optokinetics and found that most of these aspects of vision, with the possible exception of convergence, seemed to be unaffected in autistic individuals. While one study initially reported heightened visual acuity in autistic individuals (Ashwin et al., 2009) these results were questioned in terms of the technological limitations of the experimental setup (Bach and Dakin, 2009) and failed to replicate when carried out again by the same and an independent lab (Bölte et al., 2012; Tavassoli et al., 2011). Thus, there does not appear to be any strong evidence that differences in low-level visual acuity are present in autistic individuals.

This suggests that the widely reported atypicalities in the perceptual experiences of autistic individuals (Bogdashina, 2016) may instead be driven by high-level differences in how perceptual information is processed and integrated in the visual system (Iarocci and McDonald, 2006). While it has been suggested that the heightened perceptual sensitivities reported in autism may predispose autistic individuals to developing talents (Baron-Cohen et al., 2009a; Happé and Vital, 2009), the results discussed above should be viewed as differences in the style of perceptual processing rather than regarding autistic individuals as 'better' or 'worse' at aspects of perception. This can be seen in cases where the occurrence of heightened perceptual sensitivity has been linked to difficulties in other aspects of cognition, such as increased discrimination of similar stimuli (Plaisted et al., 1998a) potentially being associated with difficulties in category formation and generalisation (Alderson-Day and McGonigle-Chalmers, 2011; Hartley and Allen, 2014, 2015; Plaisted, 2015). Links between enhanced attention to detail and difficulties with sensory perception have also been proposed (Baron-Cohen et al., 2009a), highlighting why we should move away from a simplistic view of perceptual differences as simply better or worse *per se*.

1.2 Sensory issues in autism

Beyond the social difficulties experience by autistic individuals (Mundy et al., 1986), one of the most widely reported features of the condition is atypical sensory function. Sensory processing difficulties have been found to occur in 95% of autistic children (Tomchek and Dunn, 2007) and increased rates of sensory processing difficulties are also found in autistic adults (Tavassoli et al., 2014). These sensory difficulties have been identified in autistic individuals very early on in development, with some studies reporting atypical sensory processing in high-risk infants who were only 6 months old at the time of testing and would go on to be diagnosed with autism later on in their development (Estes et al., 2015). Sensory issues have been reported in autism across all the sensory domains (Robertson and Baron-Cohen, 2017), with reports of autistic individuals displaying atypical sensory processing in taste (Tavassoli and Baron-Cohen, 2012), smell (Galle et al., 2013), touch (Puts et al., 2014), hearing (Bonnel et al., 2003) and sight (Dakin and Frith, 2005; Simmons et al., 2009). In adult populations, self-reported sensory issues have been found to be elevated in autistic individuals (Tavassoli et al., 2014) as well as being linked to higher-levels of autistic traits within the general population (Robertson and Simmons, 2013). The link between sensory sensitivities and autism is complex, with a large amount of heterogeneity across autistic individuals (Hazen et al., 2014) as well as high variability within individuals (Grandin, 2009). The extremes of sensory sensitivities are *hypo*-sensitivity, in which an individual's responses to stimuli may be reduced or delayed, and *hyper*-sensitivity, in which individuals have heightened sensitivity to stimuli. These two features of sensory sensitivities can lead to particular aspects of behaviour commonly displayed by autistic individuals. Hypo-sensitivity can lead to sensation seeking, where an individual may show an intense interest in specific sensory stimuli or behaviours (Baker et al., 2008; Crane et al., 2009) and hyper-sensitivity can lead to sensory overload, where individuals are overwhelmed by external stimuli (Jones et al., 2003).

It has been suggested that the heightened sensory sensitivities often reported in autistic individuals could in fact lead to other aspects of the autism phenotype such as increased attention to detail. This could potentially explain reports of an association between autism and talent (Baron-Cohen et al., 2009a). However, while there have been suggestions of a link between sensory issues and intact or heightened abilities in autism (Shah and Frith, 1983), sensory issues are generally thought to have an adverse effect on both the individuals who experience them (Plimley, 2007) and their families (Bagby et al., 2012; Schaaf et al., 2011). Sensory difficulties are known to have a negative impact on the lives of autistic individuals (Leekam et al., 2007) and have been shown to be associated with the social difficulties that many autistic individuals experience (Hilton et al., 2010). It has also been suggested that

sensory issues in autistic individuals might lead to increased levels of anxiety (Green and Ben-Sasson, 2010). A potential causal relationship between sensory issues and anxiety could explain the high prevalence of anxiety disorders in both children and adults with autism (Kerns and Kendall, 2012; Leyfer et al., 2006; Lugnegård et al., 2011).

These two clinical features, sensory sensitivities and anxiety, have recently been found to interact with a construct called 'intolerance of uncertainty', which refers to an aversion to uncertainty or instability in day-to-day life (Boulter et al., 2014; Chamberlain et al., 2013; Maisel et al., 2016; Neil et al., 2016). This construct tends to be elevated in autistic individuals (Chamberlain et al., 2013) and has been found to correlate with anxiety (Boulter et al., 2014) and sensory issues (Wigham et al., 2015). Interestingly, it has been reported that intolerance of uncertainty significantly predicted sensory issues in autistic children after the effects of anxiety are taken into account (Neil et al., 2016). This interaction between intolerance of uncertainty, anxiety and sensory issues indicates that it may be possible that sensory issues emerge as a result of more general information processing differences in cognition (Marco et al., 2011; Minshew et al., 1997). This suggests that the way in which autistic individuals learn and process their external world could be key to understanding the perceptual differences observed.

1.3 Learning in autism

Autism has been frequently linked to the emergence of talent (Baron-Cohen et al., 2009a, 2007; Happé, 2018; Happé and Vital, 2009; Remington, 2017) and it has been suggested that some of the most eminent historical figures in science, such as Henry Cavendish and Paul Dirac, may have been autistic (Silberman, 2017). While some autistic individuals may show very high academic aptitude, and many are not effected by problems with learning, autism has a high comorbidity with intellectual disability (Matson and Shoemaker, 2009) and has been associated with challenges in learning (Jordan, 2013). These somewhat divergent accounts suggest that learning in autism is an important but complicated set of mechanisms which may be key to gaining a better understanding of the condition.

1.3.1 Statistical learning

Learning involves a complex and multifaceted set of processes, which operate across a number of different levels (Anderson, 2000; Squire, 1992). One particular type of learning that may be relevant to autism is implicit learning, which has been recognised as a key mechanism in social processing, language development and motor skills (Meltzoff et al.,

2009). Implicit learning refers to the acquisition of implicit forms of memory, which occur when information is stored in the brain and can influence decisions without being explicitly retrievable (Schacter, 1987). A subset of implicit learning, involving the acquisition of probabilities and regularities in the environment, is referred to as statistical learning (Turk-Browne et al., 2005). These two constructs are considered to be driven by the same underlying mechanisms and the terms are now often used interchangeably (Perruchet and Pacton, 2006). Statistical learning occurs without any explicit effort and without conscious awareness of acquisition of knowledge from the observer. This has been demonstrated in research by the failure of observers to explicitly acknowledge awareness of any underlying patterns in stimulus presentation, but above chance identification of these patterns when assessed by means of a forced-choice paradigm (Fiser and Aslin, 2002b).

The first studies to demonstrate statistical learning reported that the detection of underlying patterns and rules in speech streams occurs in infants as young as 2 months old (Saffran et al., 1996a) and remains into adulthood (Saffran et al., 1996b). This ability, to pick up on regularities in the sounds we hear without conscious intent or awareness, is used alongside other contextual cues in language acquisition during development (Jusczyk et al., 1999). The ability to detect regularities and patterns without conscious intent extends to other types of sensory information such as non-speech sounds (Saffran et al., 1999) and visual stimuli (Fiser and Aslin, 2001, 2002a). The fact that statistical learning abilities occur across multiple domains has led some to suggest the existence of a domain general statistical learning mechanism that allows us to detect the inherent underlying structures of our external environment (Kirkham et al., 2002). As these mechanisms play an important role in language development, social processing and motor skills, statistical learning has been an area of interest for autism research.

1.3.2 Statistical learning in autism

Research into both implicit learning and statistical learning in autism has found mixed results. The majority of studies have found an absence of group differences between autistic individuals and non-autistic controls (Barnes et al., 2008; Mayo and Eigsti, 2012; Nemeth and Janacsek, 2010), but some studies have reported reduced performance in autistic individuals. Such results could be the result of other deficits in autism and not the implicit learning mechanisms *per se*. For example, motor abilities can be impaired in autism (Fournier et al., 2010), which might explain reports of impaired implicit learning in motor-sequence tasks (Gidley Larson and Mostofsky, 2008). Foti et al. (2015) carried out a meta-analysis of implicit learning studies in autism and found no differences when combining the results of 11 different studies. This was followed up by an additional meta-analysis (Obeid et al.,

2016) which set out to build on and overcome the methodological issues of the study by Foti et al. (2015). The concerns that Obeid et al. (2016) raised regarding the results by Foti et al. (2015) were due to the fact that the differences in statistical learning that they assessed were based on the extent to which reaction times reduced across blocks in which participants were presented with predictive sequences, rather than the more standard approach of comparing differences between blocks where predictive sequences occur and blocks where trials are random (Nissen and Bullemer, 1987). However, Obeid et al. (2016) still did not find any differences between the autistic and non-autistic participants in their study after correcting these methods.

In comparison to auditory and motor tasks, statistical learning in the visual domain has not been widely investigated in autism. This is surprising when one considers that a large body of research has reported significant differences in visual processing in individuals with autism (Jolliffe and Baron-Cohen, 1997; Joseph et al., 2009; O'riordan et al., 2001; Robertson et al., 2013; Shah and Frith, 1993). A recent study that looked at visuospatial statistical learning in autism reported superior task performance in adults with autism but not children (Roser et al., 2015), however the sample sizes used were very modest. Jones et al. (2018) looked at visual statistical learning in a large sample of children with and without autism. When they compared performance across participants in the two groups, no differences were found. However, when they used a discriminant function to test the similarity of the autistic participants' responses to the typically developing children's responses, they found two distinct subgroups within the autism group. They also found that the autistic subgroup that performed similarly to the typically developing children tended to have reduced levels of autistic symptoms compared to the other autism subgroup.

Recent research has also focused on understanding the neurological underpinnings of implicit learning in autism. Zwart et al. (2018a) found that their autistic individuals showed similar behavioural responses when compared to typical controls in a serial reaction time task. However, when they looked at electrophysiological activity during the task they found that autistic children tended to rely more on automatic processes than on controlled processes (measured by the relative N2b and P3 components respectively) when compared to the typically developing children, who relied on both processes to a similar extent. The results suggested that a deficit in statistical learning was not present in the autistic individuals, rather that the autistic individuals showed neural signals suggestive of an increased reliance on implicit processes. Interestingly, Daltrozzo et al. (2017) found that both electrophysiological activity and behavioural responses showed an association between statistical learning and language performance in typically developed adults, measured by receptive vocabulary and grammatical ability.

1.3.3 Reversal learning in autism

Aside from implicit and statistical learning, another domain in which learning has been assessed in autism is that of reinforcement learning. Reinforcement learning refers to the process by which situations or events are mapped to specific actions that lead to the maximum possible reward (Sutton and Barto, 1998). A number of studies have looked at reinforcement learning mechanisms in autistic individuals, again yielding mixed results. Solomon et al. (2011) used a probabilistic reinforcement learning paradigm in adults with autism and non-autistic controls. The authors reported that, despite initial differences in learning rates, by the end of the session the two groups had reached similar levels of performance. This highlights the importance of assessing learning progression across tasks in order to gain a better insight into potential differences. Solomon et al. (2014) used functional magnetic resonance imaging (fMRI) to look at neural activation in autistic individuals during a probabilistic selection task. Their task had three probability levels for the pairs that participants were presented with, which differed by the likelihood that participants were given correct versus incorrect feedback for the pair matching. Autistic individuals had a lower level of accuracy on high-probability pairs but matched controls in the other conditions. Autistic individuals also showed increased activity in the anterior cingulate and orbito-frontal regions during the feedback phase when compared to control participants.

South et al. (2012) presented a reversal learning task in which participants were conditioned to respond to an air puff and found that autistic individuals were slower to update their responses following a reversal. In another probabilistic reversal learning task, D'Cruz et al. (2013) found that autistic participants showed a tendency to initially respond to reversals in a similar manner to controls but were more likely to later revert back to previously preferred responses. Similar to the finding by D'Cruz et al. (2013), Miller et al. (2015) looked at set shifting in a large number of autistic individuals and found that while the autistic individuals initially shifted sets, they showed difficulties in maintaining the new response sets in comparison to the control participants. They extended this finding to show that difficulties in maintaining new response sets were also related to the severity of self-reported levels of restricted and repetitive behaviors. One of the more consistent findings from the reinforcement learning literature, is that autistic individuals tend to respond slower to reversals or updates in associations during learning. These difficulties in reversal learning tasks point towards potential differences in how autistic individuals process probabilistic information and, in particular, how they handle deviations from their previous expectations. As these findings come from studies in which associations are explicitly taught and reinforced to individuals, it is not clear whether a similar pattern of behaviours would be seen in statistical learning as studies looking at this domain in autism have tended to focus on deterministic contingencies.

Chapter 2

Perceptual inference in autism

The literature summarised in the previous chapter suggests there is a lack of evidence to suggest significant differences in visual acuity exist between autistic and non-autistic individuals. Recent accounts have suggested that low-level sensory processing differences may not be present in autistic individuals and that the reported perceptual atypicalities are instead driven by differences in the relative weight given to sensory signals at higher-levels of perception (Pellicano and Burr, 2012b; Tavassoli et al., 2014). This fits with the widely acknowledged view that visual perception is a process of unconscious inference about the state of the external world which acts on noisy sensory information (Bar, 2004).

Hermann von Helmholtz was an early pioneer of the view that visual perception involves higher order processing of ambiguous retinal images. He suggested that vision was a process of finding the most likely state of visual stimuli based on both the sensory information being received and the previous experiences of the observer (von Helmholtz, 1866). This view of vision, as a process of testing hypotheses about the state of the world, has since been strongly advocated and we now understand perception to be heavily influenced by our expectations of the external environment (Seriès and Seitz, 2013a). These expectations help to solve any ambiguities in the incoming sensory information and enable us to process visual scenes in a fast and efficient way.

2.1 Bayesian models of perception

When information that aids perception is provided to an observer, it can be classed as top-down perceptual processing. Information in top-down processing can be both explicit, such as direct instructions to orientate towards specific stimuli, or implicit. Examples of implicit information guiding top-down processing can be seen in variations of visual search tasks where the detection of targets is facilitated by similarities in the appearance of targets in

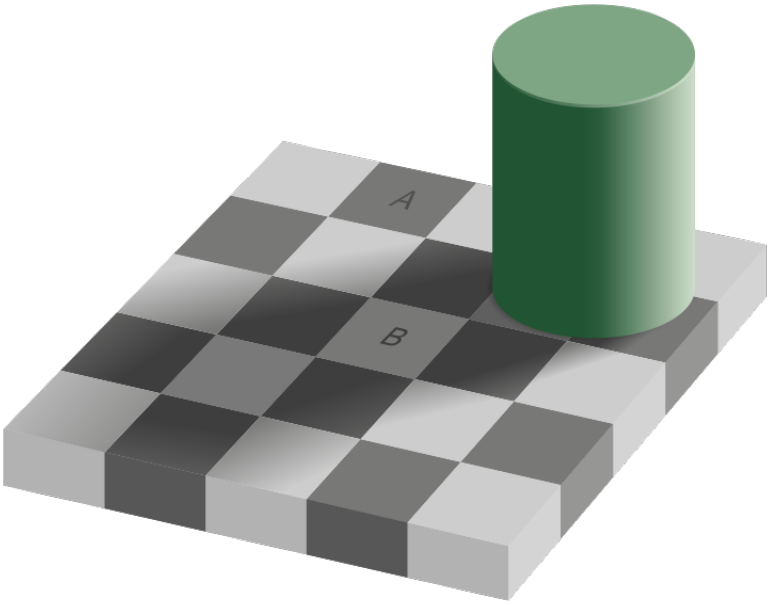


Fig. 2.1 The Adelson Checkerboard Illusion (Weiss and Adelson, 1995) demonstrates how expectations can influence perception. In the figure, the two squares 'A' and 'B' are in fact the same shade of grey. Our expectation that shadows make objects appear darker than they are leads us to account for this when processing the image, hence why square 'B' is perceived as lighter.

previous trials (Kristjánsson et al., 2002) or the spatial context of the visual search display (Chun and Jiang, 1998). It has long been understood that top-down processes play a vital role in everyday visual perception.

Attempts to model these processes mathematically have led to support for the use of Bayes' theorem (Bayes et al., 1763), a rule in probability theory which relates conditional probabilities, to explain the processes involved in visual perception (Knill and Richards, 1996). These so-called Bayesian accounts of perception suggest that visual perception is an interaction between incoming sensory information and previously acquired prior knowledge that is used to 'fill-in' gaps in a predictive manner. Bayes' theorem can be used to estimate the likelihood that an observer's perceptual hypothesis about the state of the external world, H, is true given the incoming sensory data, D. This can be stated mathematically with the following equation:

$$P(H|D) = \frac{P(D|H)P(H)}{P(D)} \tag{2.1}$$

The probability of a particular perceptual hypothesis being true (e.g. that a specific visual target is present) is represented by $P(H)$. The probability that the observer receives

the incoming sensory information is $P(D)$. $P(D|H)$ gives us the probability that we would receive the sensory input D if the hypothesis H was true (that we were indeed observing the specific visual target). $P(D|H)$ is frequently referred to as the likelihood and $P(H)$ as the prior. We can combine these as shown above, to give us $P(H|D)$, the probability that hypothesis H is true given the incoming sensory information D (often referred to as the posterior).

While this process is thought to aid vision generally, hence why it may have evolved (Geisler and Diehl, 2003), there may be cases in which prior experiences have maladaptive consequences in which they could cause 'false' perceptions. This is seen in the existence of visual illusions (Summerfield and Egner, 2009) such as the Adelson Checkerboard Illusion (as shown in figure 2.1), which occurs as an unwanted by-product of prior expectations which usually facilitate the perception of colour. A possible explanation for this illusion is that we have learnt to adjust our perceptions of colours based on the current lighting conditions. If a given object was observed as being in particularly bright sunlight or, in the case of the checkerboard illusion, in a dark shadow, then we adjust the colour we perceive to accommodate for this (as is illustrated in figure 2.2)[1].

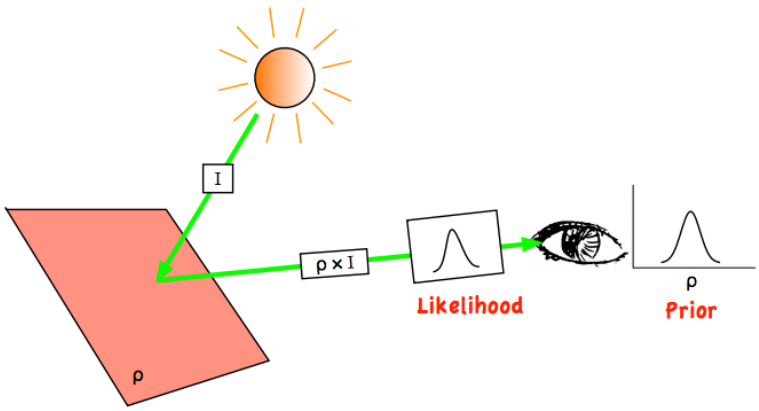


Fig. 2.2 Figure taken from Feldman (2014) demonstrating the colour estimation model suggested by Brainard et al. (2006). In this model, the prior experience, p, of a particular illuminant, I, is used to estimate the true colour of a surface based on the incoming sensory information.

[1]For further illusions caused by illumination cues see Gegenfurtner et al. (2015) and Lafer-Sousa et al. (2015)

2.2 Reduced influence of priors in autism

A recently proposed account of autism by Pellicano and Burr (2012b) has argued that a Bayesian framework might be useful in helping to explain the perceptual atypicalities seen in autism. This account suggests that differences in perceptual inference stem from 'atypicalities at the level of the prior'. Specifically, Pellicano and Burr (2012b) hypothesised that autistic individuals may have broader priors, which lead to fewer internal constraints occurring during perceptual inference, in contrast to typically developing individuals. The idea that autistic individuals place more weight on incoming sensory information and less on prior information is a concept that has been around for a long time (Mitchell et al., 2010; Mitchell and Ropar, 2004). However, formalising it within a Bayesian framework allows for new testable hypotheses to be generated and experimentally investigated (Brock, 2012).

The theory suggested by Pellicano and Burr (2012b), often referred to as the *hypo-priors* account of autism, was followed up by a number of other publications that expanded on and clarified these initial ideas. van Boxtel and Lu (2013) suggested that while the account given by Pellicano and Burr (2012b) offers a descriptive explanation of *why* various features of autism emerge, it does not provide a mechanistic explanation of *how* these are manifested. They suggest that the *predictive coding* framework might be a plausible way in which these processes are implemented in the brain.

Predictive coding is an account which can explain how perceptual expectations may be manifested in the brain (Rao and Ballard, 1999). This account suggests that the brain is constantly producing models of the world which are based on previous experiences and the context of the observer. These models of the external world allow for predictions to be made about incoming sensory information (Friston et al., 2014). Predictive coding describes how higher levels of the visual cortex attempt to predict activity at lower levels, while these lower level visual areas send information back to the higher levels when the predictions differ from the true activity at lower levels. These *prediction errors* orient higher level regions of the visual cortex to incoming information that is surprising and, therefore, important for the higher levels to take on board in order to improve future predictions. This framework provides an outline of how Bayesian principles might occur at the neuronal level (Huang and Rao, 2011).

Following a reply to the Pellicano and Burr paper (Friston et al., 2013), Lawson et al. (2014) give a detailed account of how the ideas suggested within the hypo-priors account manifest in the brain in terms of the predictive coding framework. In their account, Lawson et al. (2014) outline how a reduced influence of prior experiences may occur by means of altered neuromodulatory influences on the encoded precision of beliefs. Here, precision is regarded as the *expected level of uncertainty* of a belief (Yu and Dayan, 2005). They suggest

that a reduced influence of prior expectations in autism may not be a failure of prediction itself but instead a failure to express these predictions during perception due to their low precision and, therefore, weaker influence. This, they argue, means that the reduced influence of prior expectations in autism can be framed as a difference in *metacognition*.

Specifically, Lawson et al. (2014) proposed that there might be a deficit in processing sensory input that has decreasing precision in autism, together with a difficulty with processing sensory information in its correct context. The latter would lead to autistic individuals being influenced to a greater degree by current sensory information than typically developed individuals are. The distinction they make is that, according to predictive coding, a reduction in reliance on priors is more likely to stem from attenuated estimates of the level of precision of priors than from reduced priors themselves.

In another reply to Pellicano and Burr, Brock (2012) also pointed out that differences in perceptual experiences that would emerge from attenuated prior expectations could equally be the outcome of reduced noise in the sensory information being processed. This is based on the fact that increased precision of sensory information would lead to a reduced influence of prior expectations, similar to if the prior expectations were themselves attenuated (as illustrated in figure 2.3). This is similar to the point made by Lawson et al. (2014), who highlighted the importance of sensory precision *relative* to the precision of prior expectations and explained how these different potential mechanisms can be framed within the predictive coding account in terms of varying precision across different hierarchical levels.

Van de Cruys et al. (2013) also agree with the general model suggested by Pellicano and Burr (2012b), but disagree with the suggestion that prior beliefs themselves are weaker in autistic individuals. Instead, they argue that predictive coding gives an informative account of prior expectations in autism which leads to inflexible but strong predictions due to an inability to ignore prediction errors in complex and dynamic situations (Van de Cruys et al., 2014). These varying accounts show demonstrate how the exact mechanisms which lead to a reduced influence of prior expectations are still not clear. However, this set of accounts[2] are in agreement that a reduced influence of prior information in autism could explain a wide range of the features associated with the condition.

Pellicano and Burr (2012b) provide several examples of findings from the autism literature that they believe support their theory. These include reports of reduced susceptibility to visual illusions in autistic individuals (Happé, 1996; Mitchell et al., 2010). They also suggest that

[2]For the sake of simplicity, I will often refer to this set of accounts simply as the hypo-priors account, the Pellicano and Burr (2012b) account, or as Pellicano and Burr (2012b) and other related accounts. When these are subsequently referred to, I will be referring to a reduced *influence* of prior expectations and will be acknowledging not just the work of Pellicano and Burr (2012b) but the wider set of studies from Lawson et al. (2014), Brock (2012), Van de Cruys et al. (2013), van Boxtel and Lu (2013) and others.

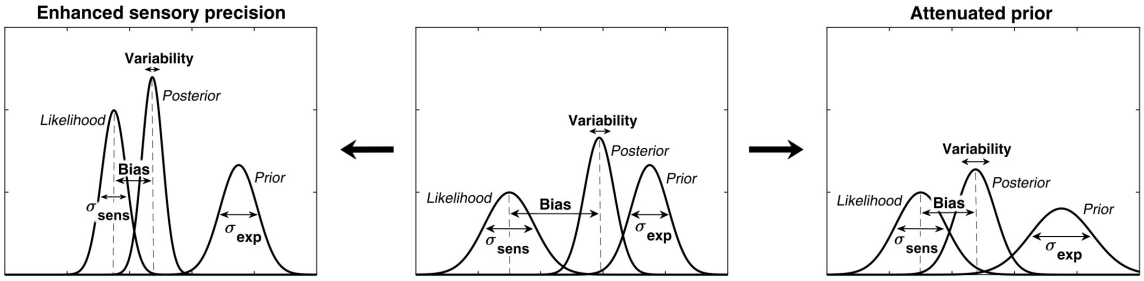


Fig. 2.3 Figure taken from Karvelis et al. (2018) showing the respective effects of enhanced sensory precision and attenuated prior expectations. The figure demonstrates how a smaller bias (reduced influence of prior expectations) can occur either due to enhanced sensory precision (as shown in the image on the left) or due to an attenuation of the prior (as shown in the image on the right).

their theory provides a good explanation for studies that find autistic individuals demonstrate superior performance in certain perceptual tasks (Loth et al., 2010; Soulières et al., 2007) due to reduced distortion in the incoming sensory signals. A number of studies since Pellicano and Burr's paper have suggested their results support the theory of an under-reliance on priors in autism. Typical individuals with higher scores on the Autism Spectrum Quotient (Baron-Cohen et al., 2001) show a reduced neural response to visual stimuli, suggesting that prior information has less of an influence on perception in individuals with higher numbers of autistic traits (Ewbank et al., 2014). Additionally, children with autism show an increased capacity for direction integration in a motion coherence task, which could reflect a reduced use of priors (Manning et al., 2015). However, a number of studies have also reported results which seem to contradict the suggestions of reduced influence of prior expectations in autism (Croydon et al., 2017; Pell et al., 2016). Based on these conflicting accounts, it appears that further empirical investigation is needed to get a better picture of how prior expectations influence perception in autistic individuals relative to the non-autistic population.

While predominantly put forward as an explanatory account of perceptual differences in autism, Pellicano and Burr's framework may also be able to account for some of the other clinical features associated with the condition. According to the ideas of Bayesian perception, incoming sensory information with higher degrees of uncertainty would lead to prior experience having a greater influence on the interpretation of information (Seriès and Seitz, 2013a). If it were the case that autistic individuals were influenced to a lesser extent by prior information, then it might explain why the autistic population have an increased tendency to be intolerant to situations and environments with high levels of uncertainty (South et al., 2014).

These predictions are also in line with those of an alternative account, the hyper-systemizing theory (Baron-Cohen, 2006; Wheelwright et al., 2006), that states that autistic individuals have a stronger preference for information that is rule-based or predictable and, therefore, an increased intolerance for information that is less lawful. As such, both theories make similar predictions about the kinds of information a person with autism may prefer. Similarly, there are overlaps in the types of behaviours predicted by Pellicano and Burr's account and those made by other theories of autism such as the weak central coherence theory (Happé and Frith, 2006; Happé et al., 2001; Happé, 1996) or the enhance perceptual function theory (Mottron and Burack, 2001; Mottron et al., 2006). One advantage in the ideas suggested by Pellicano and Burr (2012b) and other related accounts, is that it suggests a mechanism that could potentially account for all of the different aspects of autism, whereas previous theories of autism have been labelled as descriptions of single clusters of symptoms within the condition (Van de Cruys et al., 2014). The Bayesian framework also offers testable and falsifiable predictions which is not always the case in heuristic accounts (Austerweil, 2015).

2.3 Statistical learning and Bayesian perception

Both explicit and implicit processes shape the expectations which influence perception. Explicit motivations have been shown to affect how individuals perceive ambiguous stimuli (Balcetis and Dunning, 2006). We also implicitly process large amounts of information about the statistical regularities of our external environment and this information can influence how sensory stimuli are interpreted (Fiser et al., 2010a). As visual perception is regarded as a primarily unconscious and automatic process (Kersten et al., 2004) we might expect a large proportion of the prior information that is relevant to perception to be stored and retrieved implicitly (Geisler and Kersten, 2002).

While Bayesian perception is frequently referred to using terms associated with higher levels of conscious perception, the process of prior expectations and sensory information being combined to produce a percept is often an unconscious process. Bayesian perception is thought to predominantly involve the visual system using previously acquired implicit knowledge of the external world to make inferences about the environment from noisy sensory information (Summerfield and Egner, 2009)[3].

This suggests that approaches to understanding statistical learning in autism may in fact overlap considerably with the suggestions of a reduced influence of priors during perception.

[3]However, it is again worth noting that prior expectations and believed to be able to influence perception at both implicit and explicit levels (Acerbi et al., 2018).

Indeed, it has been suggested that a suitable approach to assessing the nature of prior expectations during perception is through statistical or implicit learning paradigms (Seriès and Seitz, 2013a). While research into both statistical learning and Bayesian models of perception have yet to offer up a full account of the mechanism by which these processes are carried out at the neural level, there have been proposed models, which suggest that activity in the sensory cortex could represent distributions of prior beliefs (Berkes et al., 2011; Fiser et al., 2010b). This proposed model has been suggested as a mechanism in studies approaching implicitly acquired beliefs from both the angle of Bayesian perception (Pellicano and Burr, 2012b) and statistical learning (Sanders et al., 2016).

Expectation suppression, which refers to reduced neural activity following the validation of prior expectations of a stimulus (Summerfield et al., 2008; Todorovic and de Lange, 2012), has been observed using single-neuron recordings in macaques following visual statistical learning (Meyer and Olson, 2011). The occurrence of expectation suppression is typically regarded as an example of the interaction between sensory information and expectations which is described by Bayesian models of perception (Rahnev et al., 2011; St. John-Saaltink et al., 2015). These examples suggest that the two approaches, statistical learning and Bayesian accounts of perception, may actually concern themselves with the same phenomenon, as has previously occurred in the cognitive sciences (Perruchet and Pacton, 2006).

2.4 Thesis aims

The primary aim of this thesis is to assess whether there is evidence for a reduced influence of prior expectations in autism and, if such an effect is present, to explore the nature of this difference. I will examine some of the ideas discussed in the introductory chapters across a number of different studies. This will be done at two distinct levels, using both behavioural and questionnaire data. First, I will use three distinct behavioural tasks to assess how autistic individuals acquire and use information about the probabilistic structure of their environment. These will examine different aspects of the interaction between perception and expectation, specifically looking at (i) the influence of expectations on visual attention, (ii) generalisation of acquired expectations, and (iii) the ability to update expectations in response to environmental changes. Second, I will use questionnaire measures to assess individual attitudes towards uncertainty in daily life and to explore how this related to other questionnaire-based measures of clinical traits associated with autism.

Part II

Spatial attention

Chapter 3

Rapid resumption of interrupted visual search in autism

Overview

This chapter introduces the interrupted search task and discusses how it can be used to assess the influence of prior information on spatial attention. Basic search performance in the task was analysed to test whether autistic individuals displayed superior search performance during the task.

3.1 Background

As discussed in the introductory chapters, several studies have previously reported superior performance in autistic adults during visual search tasks (Gonzalez et al., 2013; Joseph et al., 2009; O'riordan, 2004). There are also a number of studies which have shown that prior expectations can influence performance during visual search tasks (Chun, 2000; Kunar et al., 2007a; Lleras et al., 2005; Makovski, 2016; Spaak et al., 2016; Vaskevich and Luria, 2018). While the majority of these studies demonstrate a facilitatory effect of prior expectations on search performance, with increased expectations leading to faster response times, there are instances in which a reliance on prior information can also be detrimental to performance in visual search. In their visual search task, Vaskevich and Luria (2018) found that when search trials containing predictive information were mixed in with random trials without predictive information, the expectations developed in the predictable trials led to poorer performance

during the random trials and an overall increase in response times across the task. Taken together, these findings suggest that visual search may be an interesting area to investigate with regards to whether the hypo-priors account of autism extends to visual attention. Further, this could potentially offer an explanatory account of reports of superior visual search performance in autistic individuals as a reduced influence of prior expectations would be expected to lead to an increase in the relative weighting given to sensory information.

The influence of prior information on visual search has been shown across a series of studies which demonstrated how periodically removing the search display during visual search tasks can result in a unique distribution of response times, which illustrate the effects of previously acquired information on search performance. The first of these studies was carried out by Lleras et al. (2005), who asked participants to complete a visual search task in which the search display was only visible for short intervals, while being intermittently interrupted by a blank screen. By separating responses into those which occurred after a single presentation of the search display and those which occurred after two or more presentations, the authors found that the distribution of these two response types were distinct. This was interpreted as evidence for a predictive aspect of visual processing in the latter response type, as participants were able to use information acquired from previous exposures of the search display to facilitate their search performance on subsequent presentations.

Lleras et al. (2005) built on this initial finding by carrying out a number of different manipulations to the original task design in order to better understand the mechanisms of this phenomenon and to rule out alternative explanations for their results. First, they implemented an adaptation of the original paradigm in which the participants had to search for two separate targets in parallel which occurred within distinct search displays that alternated on each presentation. This version of the task produced similar response distributions from participants as the original task, which provided evidence that the results they found in the original task were not simply the product of delayed responses following previous presentations of the display. The authors also experimented with increasing the display time of their search display from 100ms to 500ms, which resulted in a stronger influence of prior information on search performance as the participants had longer to accumulate visual information.

Importantly, they were able to rule out the possibility that the effects they observed in the original study were due to a confirmation bias. This refers to a potential strategy where participants would withhold their response following the initial presentation of the search display until they could confirm their decision after viewing a subsequent presentation. The authors assessed whether this strategy was adopted by participants by inserting catch trials into the task (20% of time) in which the search display did not reappear following the initial

presentation. The absence of further presentations of the search display forced participants to respond when they realised that they weren't going to be presented with any additional information. The results from this version of the task found that responses which occurred during these catch trials were likely to have been generated by random guessing, suggesting that a confirmation strategy was unlikely to have been the cause of the observed results in the original task.

This set of findings was expanded in a second publication from the same research group (Lleras et al., 2007), in which they set out to better understand the type of information that participants acquire during the presentations of the search display prior to their responses. They were interested in whether this 'preprocessing' of visual information predominantly involved information that was specific to the target object or whether participants processed general information about the overall search display. The authors explored the exact nature of the information extracted during this preprocessing stage by including additional manipulations of the search task in which specific features of the target item were changed in-between each individual presentation of the search array. The first variation of the task that they reported involved the inclusion of trials in which the target item wasn't present until the second presentation of the search display. This manipulation removed the effects of rapid resumption following the second presentation of the search display, suggesting that rapid resumption is reliant on the accumulation of evidence specifically regarding the target rather than more general information about distractor positions in the search display. The authors also tested the effects of changing the distractor positions in-between presentations of the search display while keeping the target item in a constant position. While it was slightly reduced, the effect of rapid resumption was still present during this version of the task. This gave further support to the theory that rapid resumption predominantly involves the processing of target-specific information.

A further manipulation was included, in which there was a 50% chance of a specific feature of the target, it's colour, changing on any given presentation of the search display. Lleras et al. (2007) included two versions of this manipulation, where the feature changes were either task-relevant or task-irrelevant depending on the feature the participants were asked to respond to. The results from this version of the task showed that only task-relevant feature changes affected performance, suggesting that task-irrelevant features of the targets were not processed during the preprocessing stage. Finally, the same group published a third paper in which they used the interrupted search task to test for age-related changes in the extent to which prior information is used during visual search (Lleras et al., 2011a). They did this by classifying the individual trials for each participant into those in which rapid resumption occurred and those where standard responses occurred. They used these

response classifications to calculate a ratio score which allowed them to quantify the extent to which each individual used prior information during visual search. They found that, although search speed varied across the different age groups, the extent to which participants used prior information during search did not vary with age.

The properties of rapid resumption which were revealed by this set of studies (Lleras et al., 2011a, 2005, 2007) have been interpreted as supporting the occurrence of implicit predictions during perception within the framework of the *reentrant processing* theory of visual awareness (Lleras et al., 2007). Reentrant processing is a theory which suggests that short exposures to limited visual information lead to predictive feedback mechanisms being activated after the visual information has subsided. The account proposes that the initial visual information acquired is fed forward through increasing levels of the visual cortex, where it activates potential perceptual hypotheses in the higher-levels which are then fed back to the lower levels. These perceptual hypotheses are then assessed against any additional information processed by the visual system and the less likely hypotheses are discarded in favour of the hypotheses which best describe the current state of neural activity in the lower levels (Di Lollo et al., 2000). A failure of this process can be demonstrated in masking experiments, particularly the nature by which an increased masking effect occurs when masks are perceptually similar to the initial stimuli, which supports the view that feedback mechanisms are involved in moving information from the sensory systems to conscious awareness (Breitmeyer and Öğmen, 2006). Essentially, the reentrant processing theory can be thought of as an explanatory model of predictive coding and feedback processes during visual processing (Rauss and Pourtois, 2013). The authors of the original rapid resumption study (Lleras et al., 2005) suggest in a later account that when the results from their study are considered from the perspective of reentrant processing, rapid resumption is likely to occur as a result of the facilitatory effects of implicit predictions about the target item based on the limited information obtained during short viewings of the visual display (Enns and Lleras, 2008). These interpretations suggest that the interrupted search task used in these studies is a suitable paradigm for assessing the effects of prior information on attention in autistic individuals. Therefore, I ran a study looking at the performance of autistic and non-autistic individuals during an interrupted search task which replicated the methods used in earlier studies (Lleras et al., 2011a, 2005, 2007; Spaak et al., 2016). In this section I will present the results of this study across 3 chapters. The present chapter will focus on the basic search performance of autistic and non-autistic individuals during the interrupted search task, the second chapter will look at the effects of rapid resumption to assess the extent to which prior information is used during visual search in both groups and the final chapter will evaluate

and expand on the previous methods used to quantify the extent to which prior information is used during visual search.

3.2 Methods

3.2.1 Participants

A total of 51 male participants completed the interrupted visual search task. All participants were right handed and had normal or corrected-to-normal vision. 24 of these participants had a diagnosis of an autism spectrum condition. Participants with a diagnosis of an autism spectrum condition were recruited from the Cambridge Autism Research Database (CARD) and control participants were recruited from the Cambridge Psychology Volunteers Database or through classified adverts on websites such as Gumtree. There were no significant differences between the two groups on age (Control group, $M = 30.42$, $SD = 9.18$; Autism group, $M = 34.96$, $SD = 8.26$; $t(49) = 1.830$, $p = 0.073$) or IQ (Control group, $M = 114.11$, $SD = 11.97$; Autism group, $M = 112.54$, $SD = 13.96$; $t(49) = 0.429$, $p > 0.3$).

3.2.2 Stimuli presentation

Stimuli were presented using the Psychtoolbox extension (Brainard, 1997; Kleiner et al., 2007) in MATLAB (MathWorks, 1989). Stimuli were displayed on a 24" monitor running at a resolution of 1920x1080. Participants were sat with a viewing distance of 60cm from the screen in a darkened room.

Overall the stimuli presented and procedure used in this study closely match the methods outlined in experiment 1 from Lleras et al. (2005). Participants were required to locate a target T shape within an array of L shapes. Trials either contained 16 visual items (1 target and 15 distractors) or 32 visual items (1 target and 31 distractors). An even amount of 16 and 32 item trials were presented to each participant in a random order.

Items were presented within a centrally positioned white square which subtended a 9° visual angle. The area of the screen outside of the central square was coloured grey. Item positions were generated by randomly placing them inside an invisible 6 x 6 grid. The height and width of each invisible cell within the grid was 1.5°. During display generation, items were initially placed centrally within their grid positions and then a random amount of jitter ($\pm$0.2) was applied to this initial position in order to avoid the objects being collinearly aligned.

After generating item positions, one of the items was selected at random to be the target item and the others were presented as distractor items. All items were generated using two

lines of equal length at 90 degrees to each other, with target 'T' shapes placing the second line in the middle of the first line and distractor 'L' shapes placing the second line at the end of the first line. Each of the line segments within the items subtended 0.5° of visual angle. The orientation of each item was randomly selected from four possible options (at 90 degree rotations). Items could be either blue or red in colour, and were balanced to ensure an equal number of items of each colour in the display.

3.2.3 Procedure

During each trial, a new search display was generated using the methods detailed above. Trials were preceded by a fixation cross in the centre of the screen for 500ms. The search display was shown for 100ms at a time with a 900ms blank display period in between. Blank display periods showed a white square without any of the search items present. Each cycle of a 100ms search display presentation and 900ms blank display will be referred to as an epoch (Rensink, 2000). Trials terminated after a total of 8000ms without a response or as soon as the participant responded. This meant that on each trial the search display would be visible for a maximum of 8 times (8 epochs). Participants were shown feedback on each trial which stayed on the screen for 1000ms. This procedure is demonstrated in figure 3.1.

Participants were given instructions on the screen which were repeated verbally by the experimenter. Once the participants were happy with the instructions, they were given 15 practice trials to do. After completing the practice trials, all participants completed a control task designed to assess their baseline reaction time. The control task consisted of 30 trials in which a target object appeared without the addition of any distractor objects. Participants were asked to report the colour of the target shape (red or blue) as quickly as possible by pressing the 'z' key for a blue target or the 'm' key for a red target. Coloured stickers were placed on the keys to indicate which key corresponded to which colour.

After completing the control task, participants were given a short break before starting the main task. In the main task, participants were again required to report the colour of a target T shape. However, these T shapes were now presented alongside distractor L shapes. Participants completed a total of 10 blocks of 30 trials, it was apparent that the required effects could be obtained from a reduced number of trials [1]. Each block was followed by a 30 second rest period. The duration of the full session including the instructions, practice trials, control task and main task was approximately 30 minutes.

[1] After initial piloting using the same number of trials as described in Lleras et al. (2005). To minimise the risk of fatigue and unnecessary effort from the participants, the overall number of trials was reduced to 10 blocks of 30 trials.

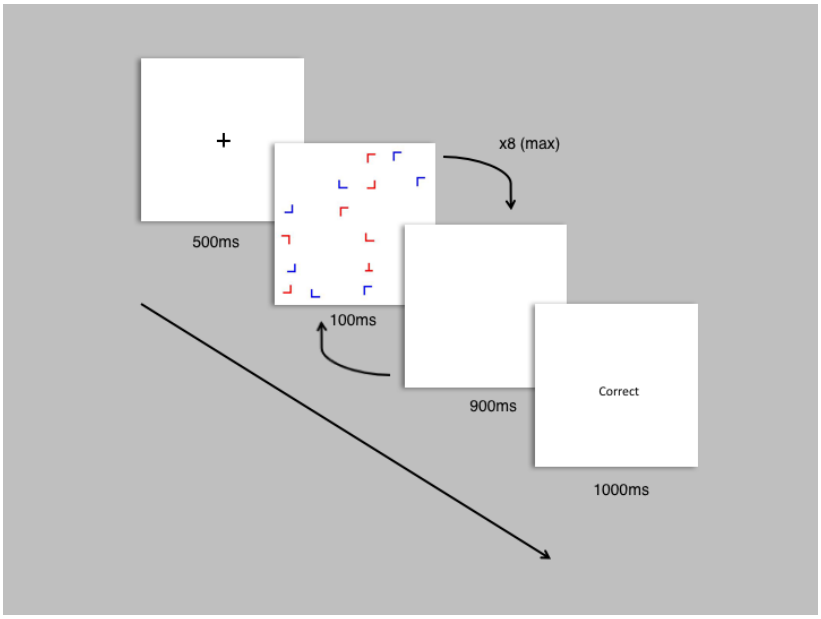


Fig. 3.1 Diagram showing the stimuli sequence for any given trial. At the start of each trial, participants are presented with a fixation cross for 500ms. After the fixation cross, the search display is presented for 100ms followed by a 900ms interval with a blank screen. The search display is shown a maximum of 8 times in total. Feedback is given for 1000ms ('Correct' or 'Incorrect') once the participant responds or the trial timed out (8000ms from initial presentation of the search display).

3.3 Results

3.3.1 Control task

Before carrying out the main task, all participants were asked to complete a short control condition of the task in which they were asked to identify the colour of the target in the absence of distractors. Data from this control condition was analysed for all participants. Median reaction times were calculated for all participants to avoid issues from outlier trials (Whelan, 2008). Reaction times from trials with incorrect responses were not included in this part of the analysis.

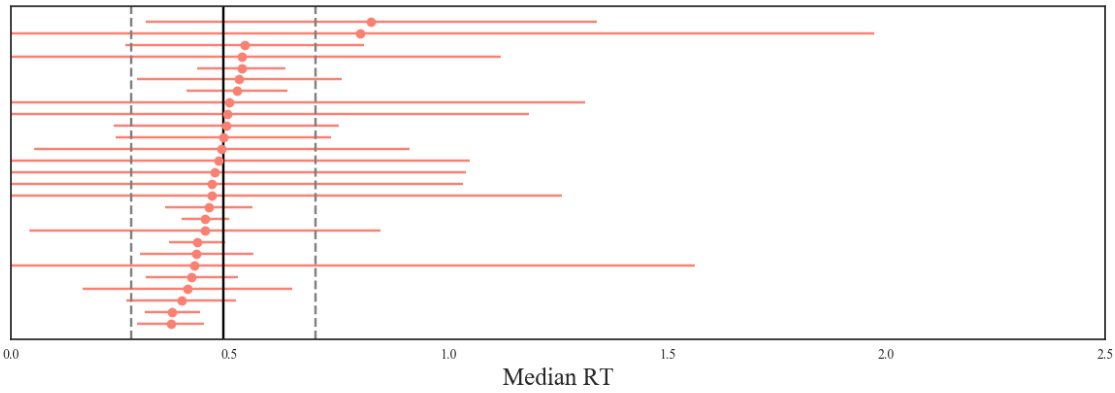
Median reaction times and standard deviations are shown for all participants in figure 3.2.[2] A Levene's test for equal variances revealed that the two groups had unequal variances ($F = 6.13$, $p = 0.017$), therefore a Welch's t-test was conducted to test whether the two groups had equal expected means. Control participants ($M = 0.48$, $SD = 0.097$) were found to be

[2] I will try to take a transparent approach to data visualisation within this thesis (Allen et al., 2018; Weissgerber et al., 2015). Where sample sizes will allow for it, I will present individual data points alongside summary statistics.

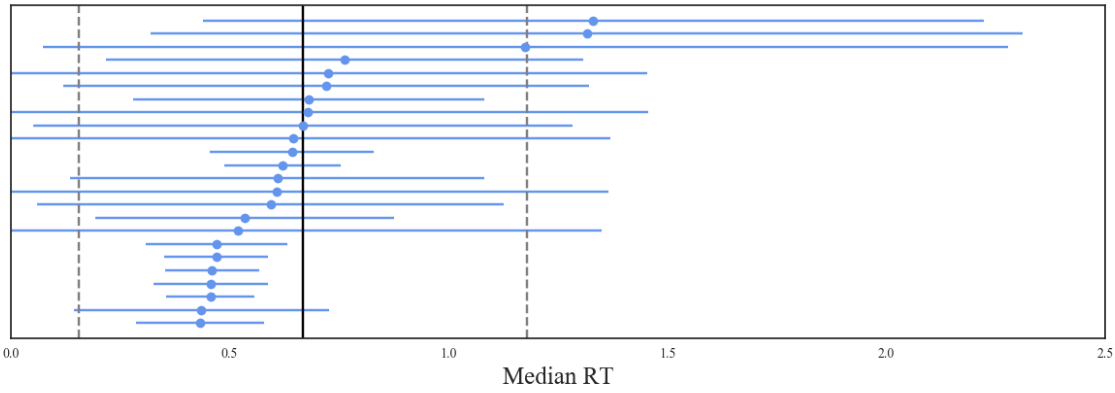
significantly faster in the control task than the autism participants (M = 0.67, SD = 0.25) at the group level (t(29.09) = -3.34, p = 0.0023).

An exclusion criteria was used to identify participants who were considered as outliers based on their baseline response times or those participants who were deemed to not be engaged in the task. The cutoff value for identifying outliers was defined as those participants whose median response times were more than 2 standard deviations from the group mean. This cutoff was calculated separately for the two groups as the participants within the two groups were sampled from unique populations (Osborne and Overbay, 2004). Additionally, participants were considered not to be engaging to a satisfactory level if their median response time fell after the second presentation of the target (RT > 1000ms). Based on these criteria, 2 participants were removed from the control group and 3 from the autism group. These participants were not included in any subsequent analyses.

Following the removal of these outliers, the previous analysis to determine whether the two groups differed on the control task was repeated. The Levene's test revealed that the two groups still had unequal variances (F = 16.19, $p < 0.001$) and so a Welch's t-test was used again to test whether the two groups had equal expected means. Control participants (M = 0.46, SD = 0.05) were found to be significantly faster in the control task than the autistic participants (M = 0.58, SD = 0.11; t(26.8) = -4.69, $p < 0.001$). The fact that this result remained suggests that the difference in performance between the two groups was not driven by extreme cases or non-attentive participants.



(a) Control participants



(b) Autistic participants

Fig. 3.2 Median reaction times for the no distractor condition shown for all participants in the control (a) and autism (b) groups, sorted in descending order. Horizontal bars show standard deviations for each participant. Vertical solid line shows the group mean and the two dashed lines show the boundaries for inclusion in further analysis (defined as 2 standard deviations from the group mean).

3.3.2 Main task

After completing the control task, participants then moved onto the main task in which they had to find and identify the colour of a target object amidst a number of distractor objects. The initial analysis looked at basic search performance on the task by considering participant reaction times from task onset. Before analysing reaction times across the task, error rates were calculated for all participants. Accuracy scores were defined as the proportion of correct responses for each participant (with a maximum possible score of 1). Participants who had accuracy scores below 2 standard deviations of their group average were excluded from further analysis. Accuracy scores can be seen in figure 3.3, with dashed lines indicating the cutoff criteria for both groups. A single participant was removed from each group.

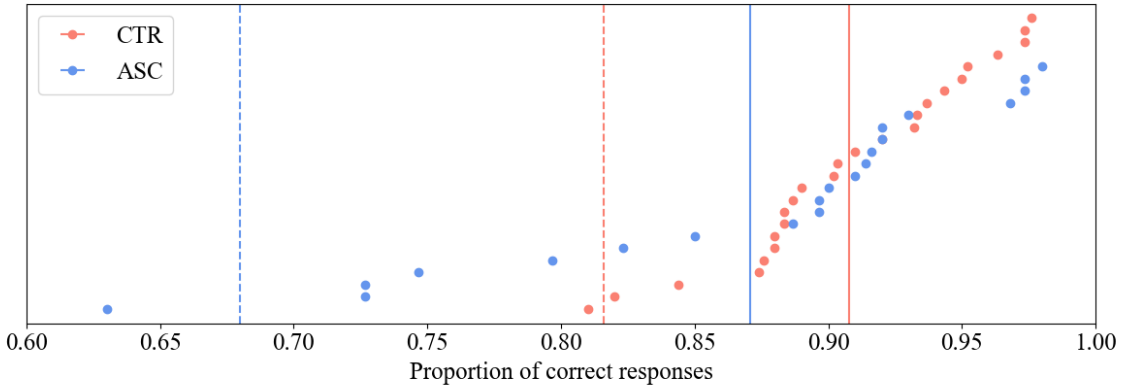
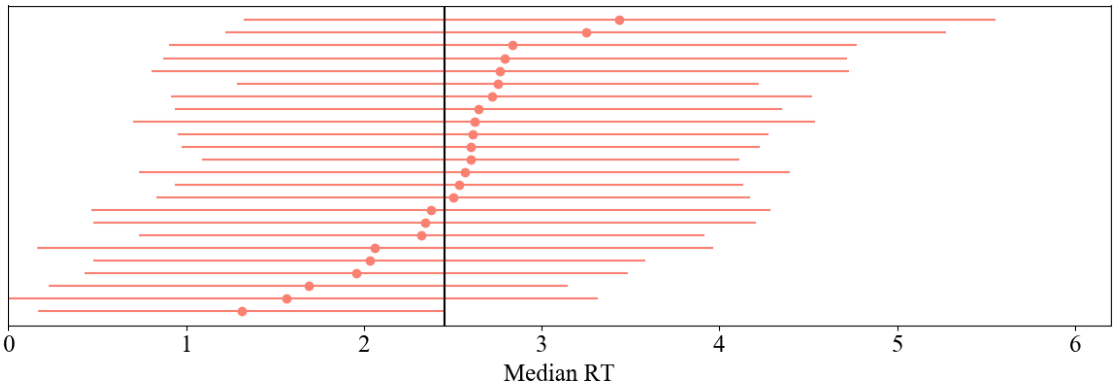


Fig. 3.3 Accuracy scores for the main search condition shown for all participants in the control (CTR) and autism (ASC) groups, sorted in descending order. Filled vertical lines show the group means and the dashed lines show the 2-standard deviation cut offs for both groups.

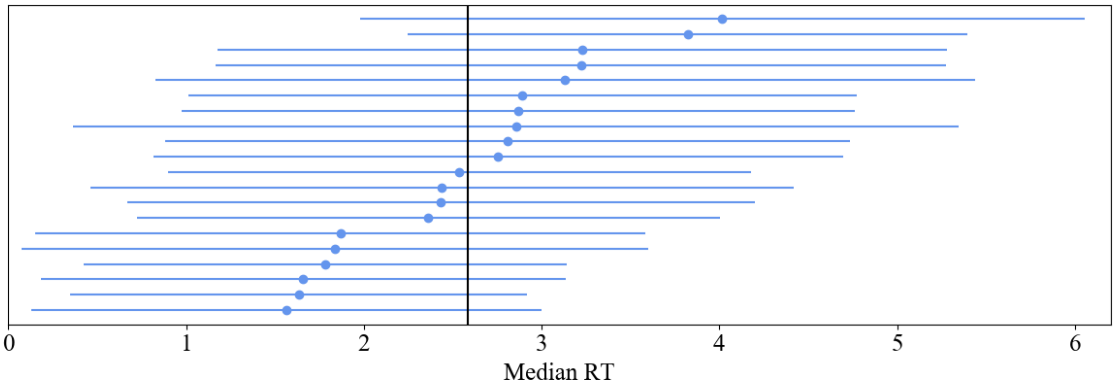
For the accuracy scores, the two groups were deemed to have equal variances ($F = 3.11$, $p = 0.085$). There were no significant differences in accuracy performance between control participants ($M = 0.91$, $SD = 0.042$) and autistic participants ($M = 0.88$, $SD = 0.08$); $t(19) = 1.55$, $p = 0.13$). After excluding participants based on poor performance the reaction time control task and for high levels of error rates, the final sample contained 24 control participants and 20 autistic participants.

Overall reaction times were then analysed for the remaining participants. These reaction times were defined as the time taken to respond in each trial from the task onset (the first presentation of the search display). The two groups had equal variances ($F = 3.77$, $p = 0.059$). and no significant differences in median reaction times were found between control

participants (M = 2.45, SD = 0.49) and autistic participants (M = 2.59, SD = 0.71; $t(19)$ = -0.72, p = 0.47). Data for all participants are shown in figure 3.4.



(a) Control participants



(b) Autistic participants

Fig. 3.4 Median reaction times for the main search condition shown for all participants in the control (a) and autism (b) groups, sorted in descending order. Horizontal bars shown standard deviations for each participant and vertical solid line shows the group means.

3.3.3 Performance across trials

Participants' data were then assessed to determine whether an improvement in performance occurred across the duration of the task. Performance was considered in terms of both median reaction times and accuracy scores (correct response rate) in turn. Group averages in these two measures were plotted across the duration of the task to allow for visual inspection. To do this, a 30-trial sliding window (equivalent to the length of 1 block) was used to calculate moving averages across all trials. For each trial, the previous 30 trials were selected and both

the median reaction time and the correct response rate across these 30 trials were calculated. Group means for these 30 trial averages were then calculated on a trial by trial basis. Average performances were plotted separately for each group to show average reaction times across the task (see figure 3.5) as well as correct response rate (see figure 3.6).

To statistically test whether participants performance was different at the start and end of the task, trials from the first two blocks and the final two blocks of the task were used to calculate averages for the two performance measures (median reaction time and correct response rate) at these two distinct timepoints. Then 2-factor analyses of variance were conducted, for median reaction and correct response rate as the outcome variables. For both of these analyses of variance, time-point (start or end) was included as a within-subject factor and group (control or autism) was included as a between-subjects factor. The results from the ANOVAs are shown respectively in tables 3.1 and 3.2.

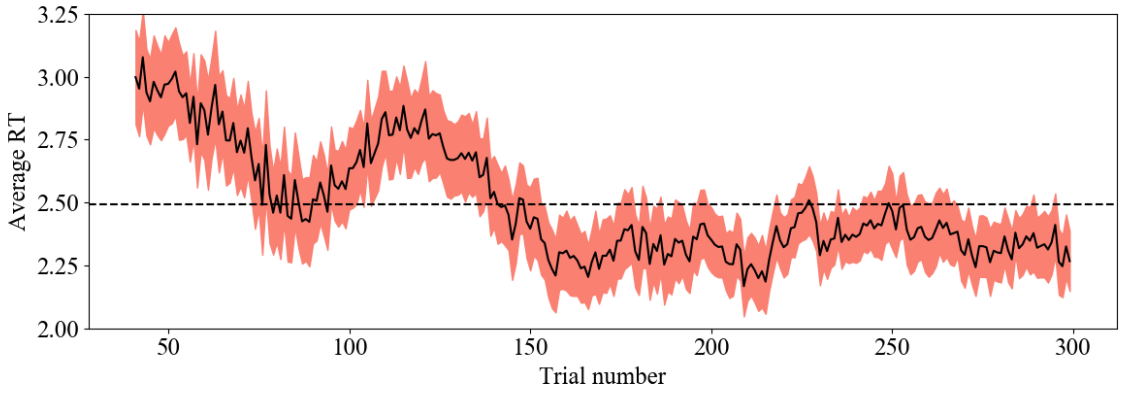
	sum sq	DF	F	PR(>F)
Group	0.037	1.0	0.084	0.77
Timepoint	3.73	1.0	8.54	0.0045
Group*Timepoint	0.42	1.0	0.96	0.33
Residual	36.68	84.0		

Table 3.1 Results from the 2x2 ANOVA with median reaction time as the dependent variable and timepoint (within-subjects) and group (between-subjects) as the two independent variables.

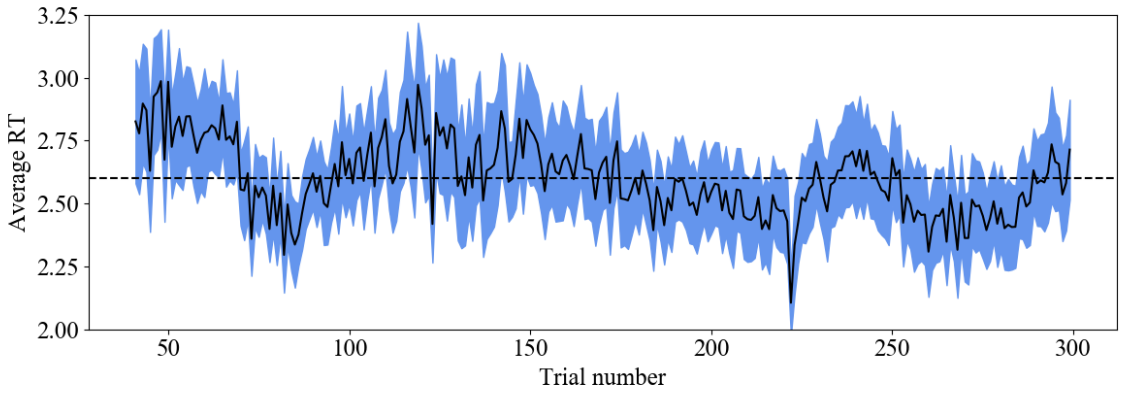
For both the reaction time and accuracy analyses, there was a significant effect of timepoint and non-significant effects of group and the group x timepoint interaction. The effects of timepoint remained significant after applying a Bonferroni correction to adjust the significance threshold due to having multiple outcome variables. The results suggest that both groups showed similar levels of improvement in reaction times and correct response rates across the task.

	sum sq	DF	F	PR(>F)
Group	0.0082	1.0	1.22	0.27
Timepoint	0.056	1.0	8.25	0.0052
Group*Timepoint	0.0044	1.0	0.65	0.42
Residual	0.57	84.0		

Table 3.2 Results from the 2x2 ANOVA with correct response rate as the dependent variable and timepoint (within-subjects) and group (between-subjects) as the two independent variables.

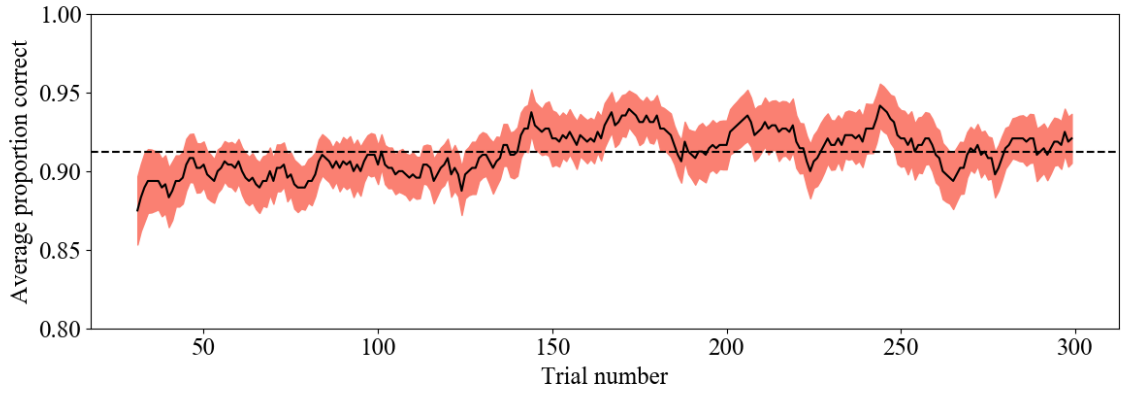


(a) Control participants

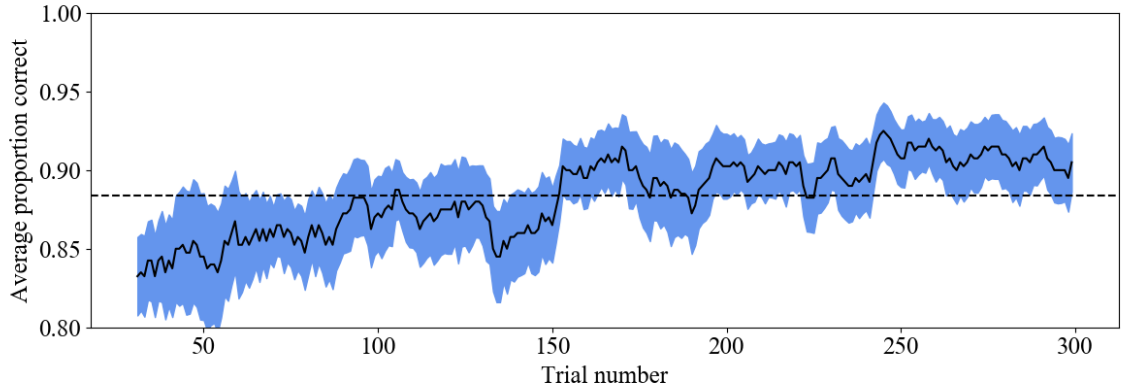


(b) Autistic participants

Fig. 3.5 Averages across participants for median reaction times across the entire main search condition. A 30-trial sliding window was used across all trials for each participant. The filled black line shows the group averages across trials and the filled areas show the standard errors across all participants in each group.



(a) Control participants



(b) Autistic participants

Fig. 3.6 Averages across participants for median reaction times across the entire main search condition. A 30-trial sliding window was used across all trials for each participant. The filled black line shows the group averages across trials and the filled areas show the standard errors across all participants in each group.

3.3.4 Effects of distractor density

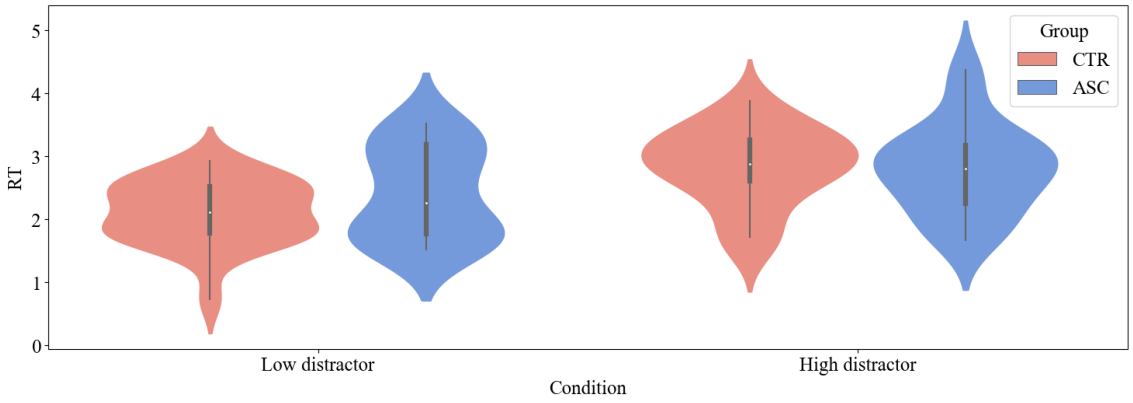


Fig. 3.7 Violin plots showing the median reaction times (RT) for low distractor and high distractor conditions shown for all participants. Box plots are overlaid to show the quartiles and ranges of each group's distribution.

To assess the effects of distractor density (the number of distractor objects present during the visual search), all trials were classified based on the number of distractor objects present in the search display. Trials contained either 15 or 31 distractor items, which will be referred to as *low distractor* and *high distractor* conditions respectively.

A 2x2 ANOVA was conducted with median reaction times as the dependent variable, condition (low distractor vs high distractor) as a within-subject factor and group (control vs autism) as a between-subjects factor. As expected, there was a significant effect of condition on reaction times, with participants responding slower on average in high distractor trials than low distractor trials. There was no significant effect of either group or the group x condition interaction. Results from the ANOVA are summarised in table 3.3 and participant data are displayed as violin plots (Hintze and Nelson, 1998) in figure 3.7.

	sum sq	DF	F	PR(>F)
Group	0.35	1.0	0.85	0.36
Condition	7.29	1.0	17.76	> 0.001
Group*Condition	0.66	1.0	1.61	0.21
Residual	34.49	84.0		

Table 3.3 Results from the 2x2 ANOVA with median reaction time as the dependent variable and distractor condition (within-subjects) and group (between-subjects) as the two independent variables.

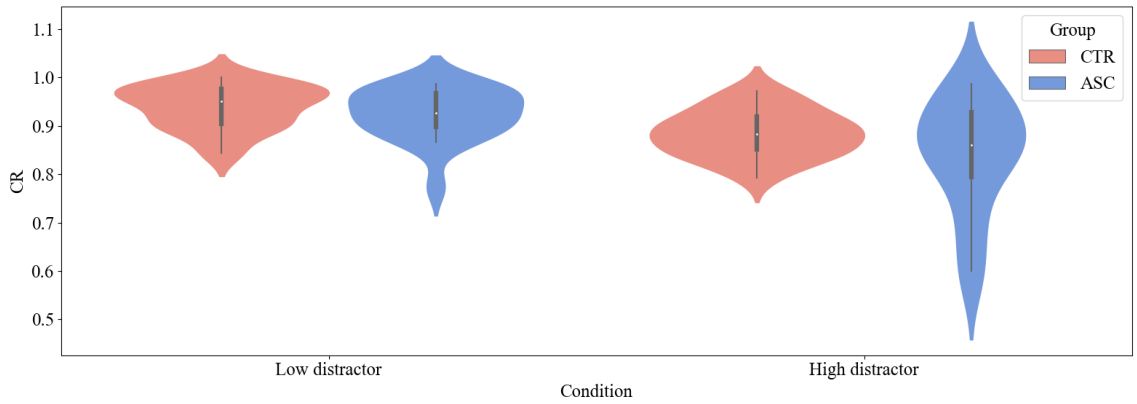


Fig. 3.8 Violin plots showing the correct response rates (CR) for low distractor and high distractor conditions shown for all participants. Box plots are overlaid to show the quartiles and ranges of each group's distribution.

	sum sq	DF	F	PR(>F)
Group	0.019	1.0	3.79	0.055
Condition	0.10	1.0	20.82	> 0.001
Group*Condition	0.005	1.0	1.03	0.31
Residual	0.41	84.0		

Table 3.4 Results from the 2x2 ANOVA with correct response rate as the dependent variable and distractor condition (within-subjects) and group (between-subjects) as the two independent variables.

Similarly, a 2x2 ANOVA was conducted with correct response rate as the outcome variable, condition (low distractor vs high distractor) as a within-subject factor and group (control vs autism) as a between-subjects factor. Similarly to the reaction time analysis, there was a significant effect of condition on correct response rate with participants making more errors on average in high distractor trials than low distractor trials. There was no significant effect of either group or the group x condition interaction. Results from the ANOVA are summarised in table 3.4 and participant data is shown in figure 3.8. Both of the main effects of condition on reaction times and correct response rates remained significant after applying a Bonferonni correction to account for multiple testing. The lack of an interaction effect between condition and group suggested that the effects of distractor density were similar across the two groups.

3.4 Discussion

In this chapter, participant responses from the interrupted search paradigm were analysed irrespective of number of presentations of the search displays the participant had observed. This allowed for me to assess basic visual search performance in the two groups, before moving on to conduct additional analyses in the following chapters which would determine the extent to which participants were influenced by prior information during the task. The results presented here also included data from a control condition in which participants were asked to identify the colour of a target item in the absence of any distractor items. This gave a measure of baseline reaction times, which could be used to gauge basic motor reaction performance. The results found that average baseline reaction times in the control task tended to be slower for autistic participants than for controls and there was a higher level of within-subject variance across trials in the autism group. This fits in with a number of findings in the literate which show that motor responses to visual stimuli tend to be slower in autistic individuals (Fukui et al., 2018; Gowen and Hamilton, 2013; Todd et al., 2009). However, it is worth noting that there is not a full consensus for this finding (Ferraro, 2016).

After considered performance in the control task, I then looked at participants' performance in the main search task. There were no significant differences in either error rates or reaction times between the two groups. Both the control group and the autism group showed improvements in reaction times and error rates during the task, suggesting that participants from both groups benefited from exposure to more trials as the task went on. This effect was comparable between the two groups. The effect of the number of distractor items present in the search display was also considered, by contrasting low- (16 item) and high-density (32 item) search trials. Participants in both groups tended to give slower responses during high-density distractor trials, suggesting that search became harder when the number of distractor items was increased. Again, the two groups did not show any differences in the extent of this effect.

Superior performances during visual search tasks have been reported numerous times in the autism literature. Expanding on work that found a visual search advantage in autistic children (O'riordan et al., 2001; Plaisted et al., 1998b), O'riordan (2004) reported superior search performance in autistic adults. They found that autistic adults performed similarly to controls during a feature search task, in which participants were required to find a predefined target that differed in all of its features to the distractor items. However, when participants were required to perform conjunction search, in which the specific features of the target occured in some of the distractor items but never in conjunction, then the autistic group outperformed the controls. Another study that reported superior search performance in autistic adults used a feature-based visual search task, in which the search display was randomised

at intervals of 500ms in order to disrupt reliance on memory during the task (Joseph et al., 2009). The authors suggest that their results indicate that the superior performance observed in autistic individuals occurs due to non-search processes such as enhanced discrimination of the features of search items in the task. The finding of superior visual search in autistic adults has also been extended to 'naturalistic' visual search tasks, in which participants were asked to perform a simulated luggage screening task (Gonzalez et al., 2013).

There are a number of possible explanations for the absence of superior search performance in autistic individuals within the present study. The task used in the present study was non-standard search task, as the search display was only shown for very short intervals between large interruptions where no stimuli were presented. It is possible that the limited time for which the search display is presented in the task restricts the period during which an enhanced discrimination ability would give autistic individuals an advantage, reducing possible differences between the two groups. Further, the fact that the interrupted search task uses feature based search, and not conjunctive search, sets it apart from previous studies that reported a difference between autistic and non-autistic individuals. It is also possible that the fact that the task is designed to elicit the use of prior information during search affects the two groups differently. The theory set forward by Pellicano and Burr (2012b) would suggest that autistic individuals would use prior information to a lesser degree than the non-autistic participants. Therefore, it is possible that this aspect of the task design gives non-autistic participants an advantage which could results in discounting any autism advantage that occurred due to enhanced discrimination. This possibility will be formally tested in the following chapters. Overall, it does not seem particularly problematic that there were no observed differences between the two groups on basic search performance.

Chapter 4

Use of prior information during interrupted visual search in autism

Overview

In this chapter, the extent to which participants were influenced by prior information during the interrupted search task was assessed. Responses that occurred with prior exposure to the search display were compared to responses that occurred without prior exposure to assess whether there was evidence of a facilitatory effect of prior information on search performance. Individual differences in the extent to which participants were influence by prior information were assessed by calculating the proportion of responses in which *rapid resumption* was thought to occur. Group differences were considered to assess whether there was evidence to suggest that autistic individuals were influenced by prior expectations to a lesser degree than controls.

4.1 Background

In the previous chapter, I introduced the interrupted search paradigm and carried out analyses to assess basic visual search performance in the autistic and non-autistic participants. In this chapter, I will conduct further analyses to assess the extent to which individuals in the two groups were influenced by prior information during the task. The primary approach of

this analysis will be based on the methods used by Lleras et al. (2005), when they initially reported the phenomenon of rapid resumption. This method involved comparing the different distributions for two distinct types of responses: those responses that followed a single presentation of the search display and those responses that followed one of the subsequent presentations of the search display. This approach will be used in the present chapter to determine whether the two groups both show the effect of rapid resumption during the interrupted search task.

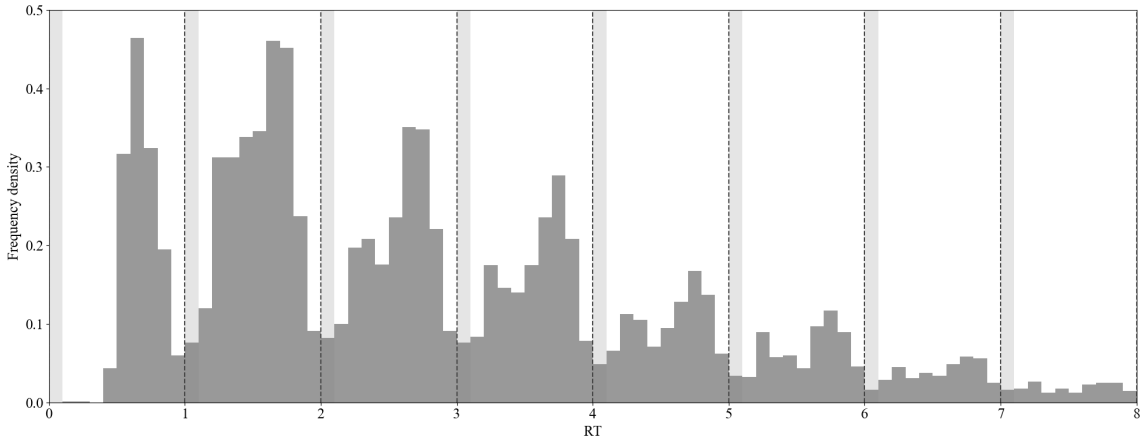
The authors of the original rapid resumption paper carried out a number of different versions of the task in order to fully establish that the effect they observed was indeed a result of prior information influencing search performance and were not artefacts of other processes (Lleras et al., 2005, 2007). This was discussed in detail in the previous chapter. As these additional findings have discounted other potential explanations for the observed effects of rapid resumption, the present analysis will use the presence of rapid resumption as an indication that prior information is used to influence search performance. I hypothesise that, based on the claims of (Pellicano and Burr, 2012b) and the other related accounts of reduced use of prior information in autism, I would expect to see an absence or reduced presence of the effect of rapid resumption in autistic individuals. Additionally, this chapter will use a method set out by Lleras et al. (2011b) to gauge individual differences in the extent to which each participant uses prior information during the task. This will allow for a group comparison to carried out to assess whether there is evidence to support the hypothesis that autistic individuals use prior information to a lesser degree.

4.2 Methods

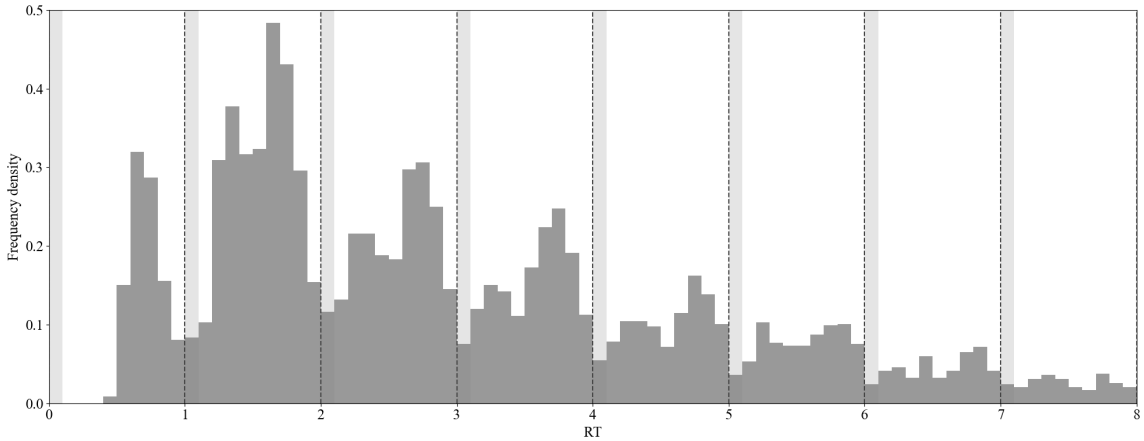
The analyses presented here extend the work discussed in the previous chapter. Previously, the only outcome measures considered for task performance were accuracy and overall reaction time (defined as the time elapsed between the first presentation of the search display and the time at which the participant responded). The effect of rapid resumption that Lleras et al. (2005) reported was only evident after considering the distributions of reaction times when they were divided into those responses that occurred following the initial presentation of the search array and those responses that occurred following subsequent presentations. This extended analysis will use the same data that are presented in the previous chapter.

4.2.1 Data pooling

Data for all response trials was pooled together for all the participants. This was done individually for the autism and control groups. Only correct responses were included in this dataset. The responses within the pooled dataset were then divided into 100ms bins across the maximum trial duration of 8000ms. A frequency density histogram showing the distribution of responses across is presented in figure 4.1. The plot shows a very similar pattern to the results of Lleras et al. (2005), with a non-Gaussian, multimodal distribution across the entire trial duration as expected.



(a) Control participants



(b) Autistic participants

Fig. 4.1 Frequency density distributions shown for the merged reaction time data for all correct responses in the control (a) and autism (b) groups. Dotted lines indicate where each epoch ends and the next begins. The light grey bars at the start of each epoch show the period for which the search display was visible.

All responses in the dataset were then labelled based on the number of times the search display had been presented before the response was given. This effectively categorised all responses into 8 different distributions for each 1000ms period (as shown by the dotted lines in figure 4.1). These 1000ms periods that follow the onset of each search display presentation will be referred to as epochs (Rensink, 2000). The distribution of the first epoch appears to be distinct from the distributions within other epochs, as was reported by Lleras et al. (2005).

4.2.2 Comparison of response distributions

To compare the distribution of responses in the first epoch to the distribution of responses in subsequent epochs, all responses were label as either *fast responses*, responses that occured within 1000ms of the first presentation of the search display (epoch 1), or *standard responses*, responses that occured following subsequent presentations of the search display (epochs 2-8). Lleras et al. (2005) carried out a statistical comparison of the distributions of first epoch responses (fast responses) and other epoch response (standard responses) by separating the responses into 100ms time bins and then conducting a Chi-squared test. However, a different approach will be used here to compare the response distributions. This is due to the fact that the Chi-squared test is arguably not suitable for this comparison as the low number of responses occurring in the first 500ms within the first epoch would lead to an insufficient number of observations in these time bins, resulting in a failure to meet one of the assumptions of the Chi-squared test (Fisher, 1922, 1924). Instead, comparisons between the distributions were carried out using a Mann-Whitney-U test (Mann and Whitney, 1947) as it allows for differences between two groups to be assessed in non-parametric samples (McKnight and Najab, 2010).

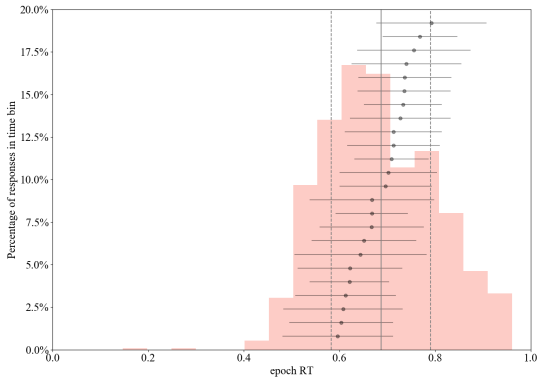
4.3 Results

4.3.1 Response distributions

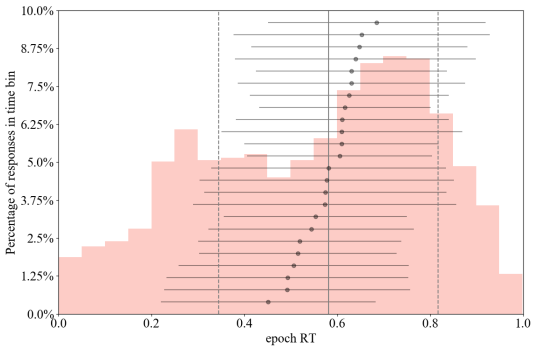
The distributions of fast and standard responses appeared to be similar to the results reported by Lleras et al. (2005). The distributions of fast responses appeared to be an ex-Gaussian distribution, which is common for reaction time distributions (Baayen and Milin, 2010; Ratcliff, 1993; Whelan, 2008), whereas the standard responses appeared to be bimodal in distribution. To statistically verify that these different distributions of reaction times were indeed non-normally distributed, a Shapiro-Wilk test (Shapiro and Wilk, 1965) was carried out on the fast and standard response distributions for the control and autism groups. All results were both nominally significant and remained significant after correcting for multiple

testing, suggesting that all distributions deviated for normality (Control group, standard: $W = 0.963$, $p < 0.001$; Autism group, standard: $W = 0.963$, $p < 0.001$; Control group, fast: $W = 0.984$, $p < 0.001$; Autism group, fast: $W = 0.979$, $p < 0.001$).

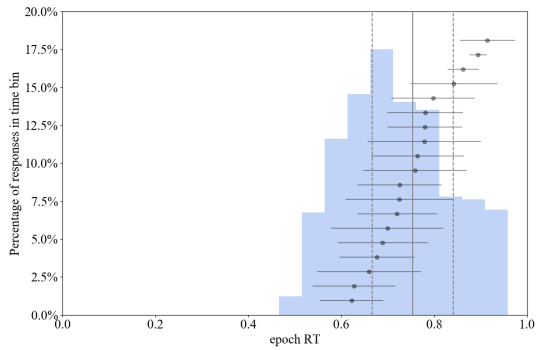
The distribution of fast responses significantly differed from the distribution of standard responses in both the control group (*Mann–Whitney* $U = 2738883$, $p < 0.001$ *two-tailed*) and the autism group (*Mann–Whitney* $U = 965321$, $p < 0.001$ *two-tailed*). Distributions of standard responses did not significantly differ between the control and autism groups (*Mann–Whitney* $U = 18089947$, $p > 0.3$ *two-tailed*). However, there was a significant difference in the distributions of fast responses between the control and autism groups (*Mann–Whitney* $U = 272461$, $p < 0.001$ *two-tailed*). All the effects reported remained significant after applying a Bonferroni correction for multiple testing. Response distributions for fast response and standard responses in both the autism and control groups are shown in figures 4.2 (a-d).



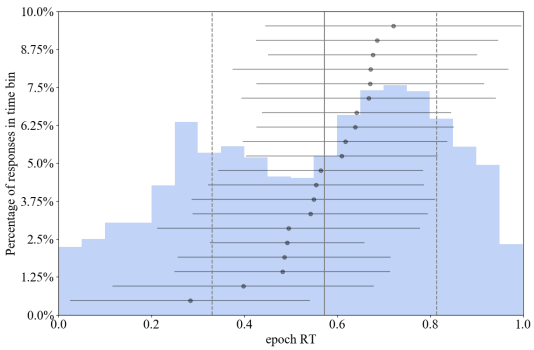
(a) Fast responses for the control participants



(b) Standard responses for the control participants



(c) Fast responses for the autistic participants

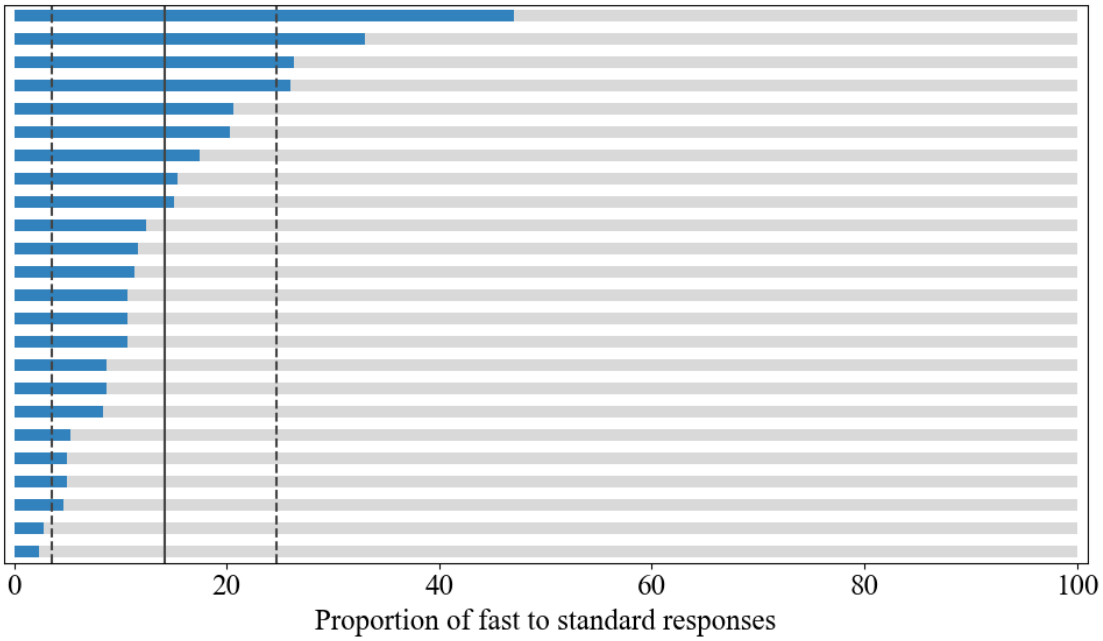


(d) Standard responses for the autistic participants

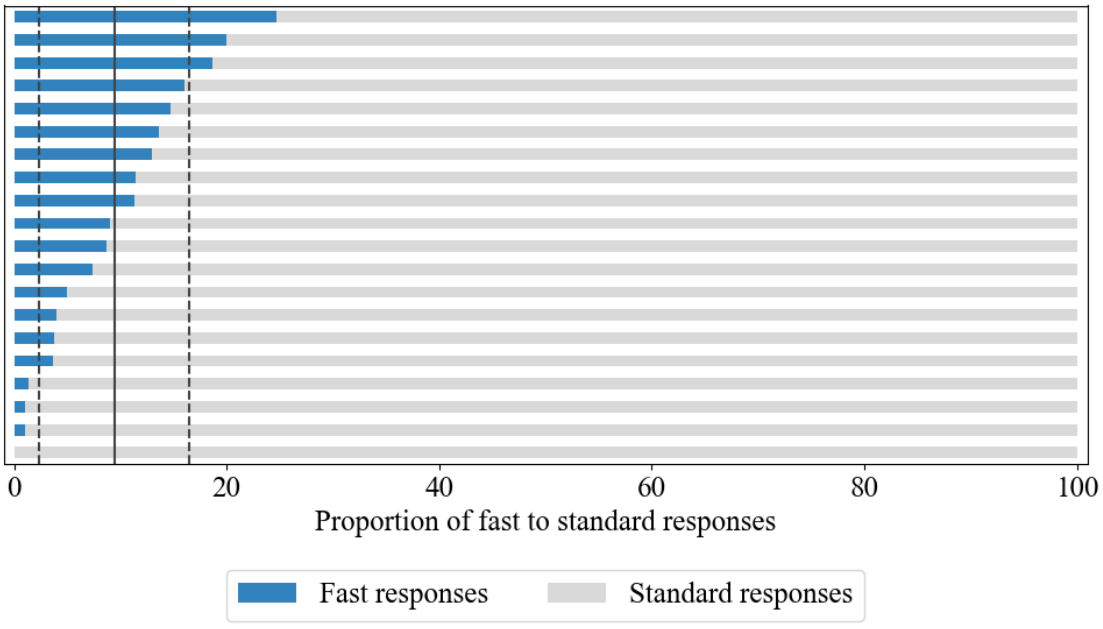
Fig. 4.2 Normalised reaction time distributions shown separately for fast and standard responses in the control and autism groups. The individual figures show the within-epoch distributions of (a) fast responses (responses in epoch 1) for control participants, (b) standard responses (responses in epochs 2-8) for control participants, (c) fast responses (responses in epoch 1) for autistic participants and (d) standard responses (responses in epochs 2-8) for autistic participants. Individual (non-pooled) normalised median reaction times and standard deviations for all participants are overlayed on top of the pooled distributions, sorted in descending order. The group averages for the normalised median reaction times within each epoch are shown as the solid vertical grey lines and the standard deviations are shown as the dashed vertical grey lines.

4.3.2 Proportion of fast responses

For the ratio of fast to standard responses, a Levene's test revealed the two groups to have equal variances ($F = 3.09$, $p > 0.3$). While the control participants tended to have a higher proportion of fast responses ($M = 14.14$, $SD = 10.57$) than the autistic participants ($M = 9.41$, $SD = 7.09$), this difference did not reach significance ($t(19) = 1.71$, $p = 0.095$). The proportion of fast responses in both the control and autism groups were considerably lower than the data published by Lleras et al. (2005) who reported that 28% of all trials were fast responses across their sample. This will be discussed in more detailed at the end of the chapter.



(a) Control participants



(b) Autism participants

Fig. 4.3 Proportion of correct response that were classified as fast or standard for all participants. The proportion of correct responses that followed the first presentation of the stimuli (fast responses) is shown in blue and the proportion of correct responses that followed the subsequent presentations of the stimuli (standard responses) is shown in grey. Average proportion of fast to standard responses is shown for each group as the solid vertical grey line, with the standard deviations shown as the dashed grey lines.

4.3.3 Association of motor reaction times with proportion of fast responses

To assess whether the rate at which participants produced fast responses was associated with basic motor reaction times, Pearson correlation tests were conducted between median reaction times in the non-distractor control task and the proportion of trials in which fast responses occurred in the main search task. This correlation was assessed separately for the two groups to determine whether the relationship between these variables differed between the two populations. There was a significant negative association between non-distractor reaction times and the proportion of fast responses in the autism group (r = -0.863, $p < 0.001$). The correlation between these two measures was found to be attenuated and non-significant in the control group (r = -0.313, p = 0.136). These two correlations are shown in figure 4.4. A Fisher transform was conducted in order to test whether the relationship between the two variables significantly differed across the two populations (Fisher, 1915), which found the difference between these two correlations to be significant (Z = 2.97, p = 0.003 *two-tailed test*). To further explore this relationship, a multiple linear regression was conducted with non-distractor reaction time as the dependent variable and proportion of fast responses, diagnostic status and an interaction term (proportion of fast responses x diagnostic status) as the independent variables. The proportion of fast responses was not a significant predictor of reaction times in the control task, whereas both diagnosis status and the interaction term were found to be significant predictors (results are summarised in table 4.1). Taken together, these results suggested that motor reaction times are related to the occurence of fast responses in the autistic participants but not in the control participants.

	coef	SE	t	p > | t |
Intercept	0.4807	0.018	25.995	0.000
PFR	-0.0015	0.001	-1.415	0.165
Group	0.2302	0.027	8.402	0.000
PFR * Group	-0.0123	0.002	-6.047	0.000

Table 4.1 Coefficient table for the multiple linear regression model of non-distractor task reaction times. Proportion of fast responses (PFR), group and an interaction term between group x PFR were included as independent variables in the model.

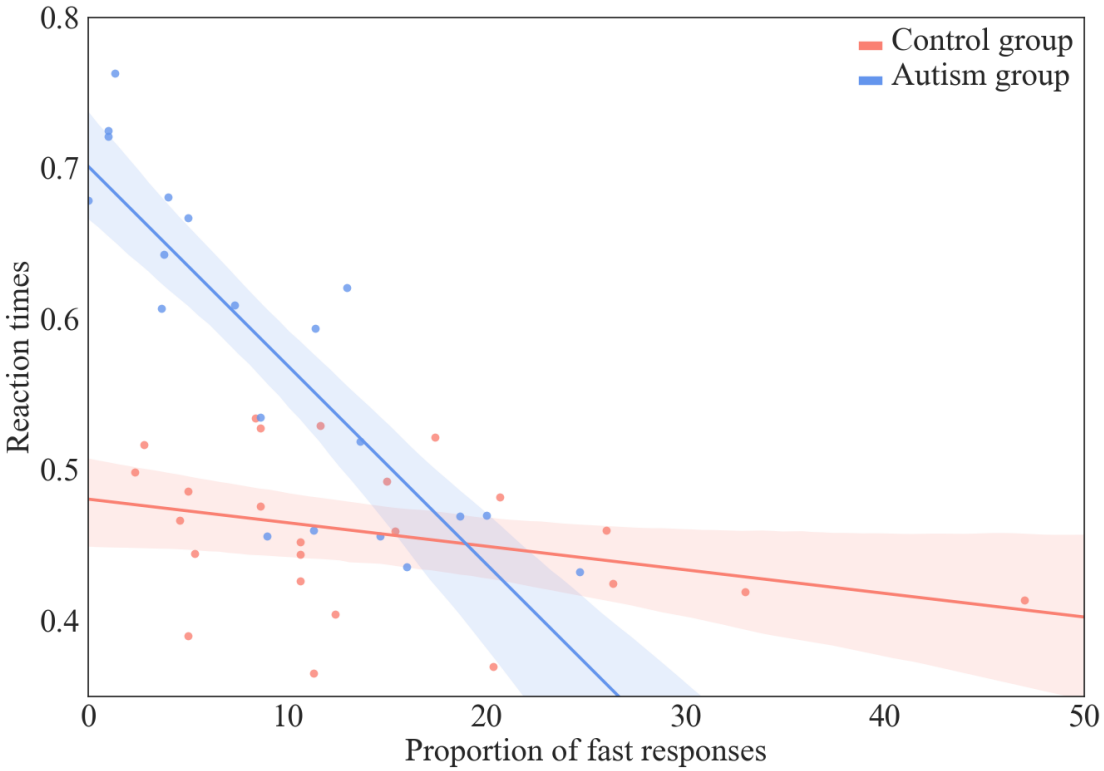


Fig. 4.4 Correlations between median reaction times in the control task and the proportion of fast responses in main task. Data are shown separately for autism and control groups.

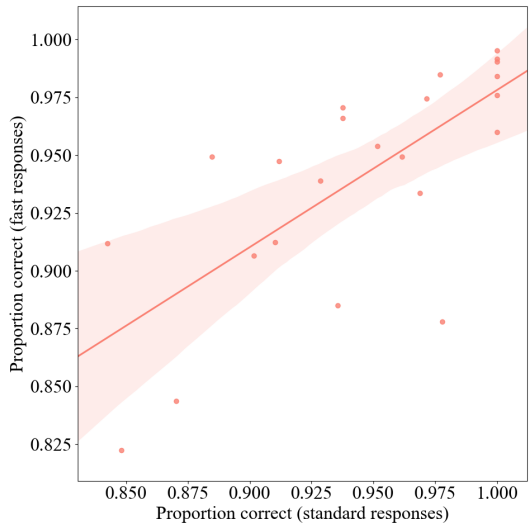
4.3.4 Association of fast response reaction times with standard response reaction times

The relationship between fast and standard responses was then investigated by looking at correlations between the two types of response using the proportion of correct responses (error rates) as well as the median within-epoch reaction times (response times). As some participants only produced fast responses on a small number of trials, any participants that had fewer than 12 fast trials were removed from this analysis. This resulted in 1 control participant and 4 autistic participants not being included in the present analysis.

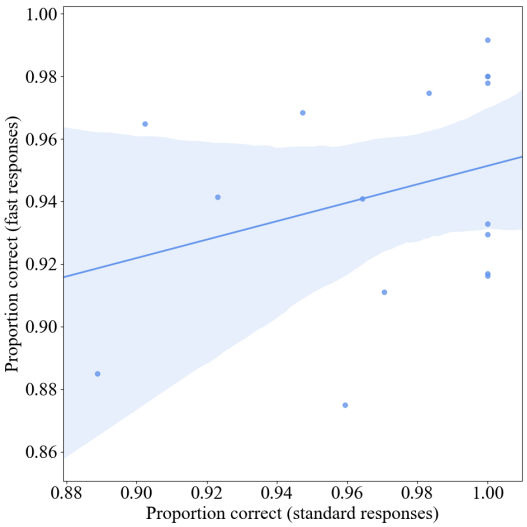
A Pearson correlation test was conducted between the proportion of fast responses that were correct and the proportion of standard responses that were correct. This was done separately for the two groups (see figure 4.5 (a) and (b)). There was a significant correlation between these two measures in the control group ($r = 0.718$, $p < 0.001$) but the relationship was non-significant in the autism group ($r = 0.311$, $p = 0.241$). A Fisher transform was conducted to test whether the relationship between the two variables differed across the two

populations, which did not find a significant difference between these two correlations (Z = 1.67, p = 0.099 *two-tailed test*).

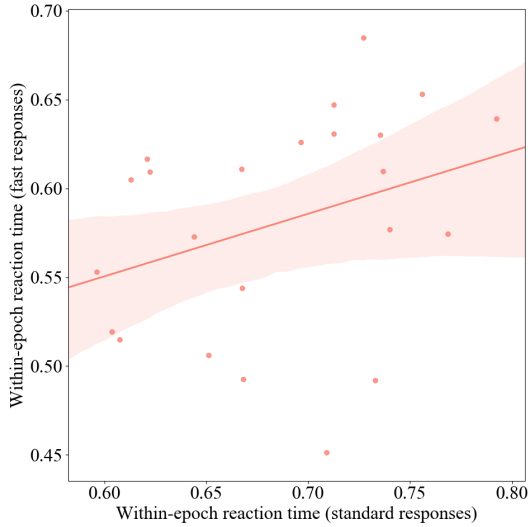
Similarly, correlation tests were conducted between the median within-epoch reaction times of fast responses and standard responses for each participant. Again, this was carried out separately for the two groups (see figure 4.5 (c) and (d)). The correlation between these variables was non-significant in both the control group (r = 0.334, p = 0.12) and the autism group (r = 0.241, $p > 0.3$).



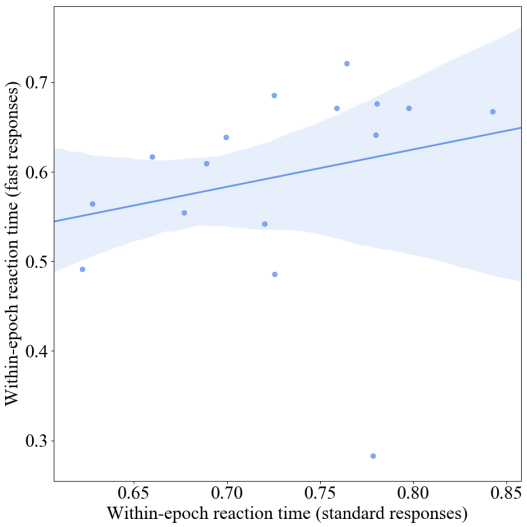
(a) Proportion of correct responses plotted for fast responses against standard responses in the control group.



(b) Proportion of correct responses plotted for fast responses against standard responses in the autism group.



(c) Within-epoch reaction times plotted for fast responses against standard responses in the control group.



(d) Within-epoch reaction times plotted for fast responses against standard responses in the autism group.

Fig. 4.5 Correlations between performance in fast response trials and standard response trials. Proportion of correct responses are shown for control (a) and autistic (b) participants. Median within-epoch reaction times are shown for control (c) and autistic (d) participants. Solid lines indicate the lines of best fit and shaded regions show the standard errors.

4.3.5 Rapid resumption responses

Relative proportion of rapid resumption responses

The spread of the standard responses showed a clear bimodal distribution, similar to results reported in previous studies using interrupted search paradigms (Lleras et al., 2011a, 2005, 2007; Shen and Jiang, 2006; Thomas and Lleras, 2009). This is suggestive of two unique underlying mechanisms producing the observed responses. Specifically, these two distinct underlying mechanisms could be driving trials in which rapid resumption occurs and trials in which rapid resumption does not occur. To assess whether group differences occurred between control and autism participants, I will quantify the proportion of trials in which rapid resumption responses occur relative to the number of trials in which rapid resumption does not occur. Lleras et al. (2011a) defined *rapid resumption responses* to be responses made within 500ms of the onset of the search display. While this cutoff value may seem arbitrary, it is based on the researchers' operational definition of rapid resumption which they defined in previous research (Lleras et al., 2005). In this chapter, the ratios of rapid resumption responses to non-rapid resumption responses will be calculated using this definition. This metric will be referred to here as the basic rapid resumption scores, or *RR-Basic*. This cutoff will also allow for standard responses to be subcategorised into trials in which rapid resumption responses occur and trials in which rapid resumption does not occur. These will be referred to as *rapid responses* and *slow responses* respectively.

RR-Basic scores were not significantly correlated with motor reaction times (as measured by the control task) in either the control group (r = -0.166, $p > 0.3$) or the autism group (r = 0.407, p = 0.083). Additionally, the correlations between the proportion of fast responses produced by participants and their RR-Basic scores were also non-significant for both the control (r = -0.375, p = 0.071) group and the autism group (r = -0.453, p = 0.052). This suggests that the extent to which an individual is influenced by previous exposure to the search display is not affected by either of these measures. However, it is worth noting that some of the correlations are close to the nominal significance threshold so it is not clear whether this is a true absence of relationship or whether the tests are underpowered.

A Levene's test revealed that the RR-Basic scores had unequal variances across the two groups (F = 4.99, p = 0.031) and so a Welch's t-test was used again to test whether the two groups had equal expected means for RR-Basic values. Control participants (M = 0.40, SD = 0.078) did not significantly differ from the autism group (M = 0.425, SD = 0.126; t(30.6) = -0.73, p = 0.47). The distributions of scores for both groups are shown in figure 4.6

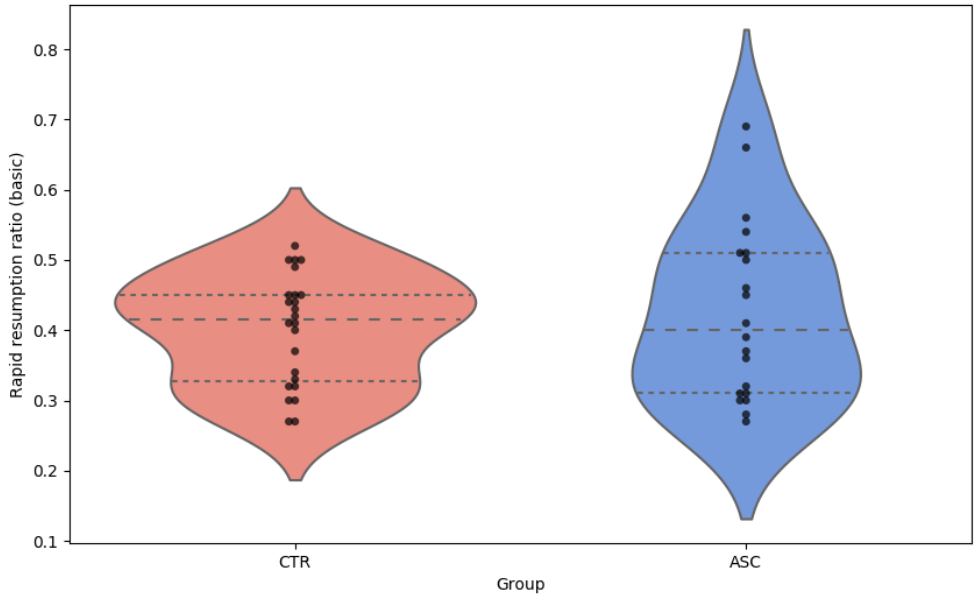


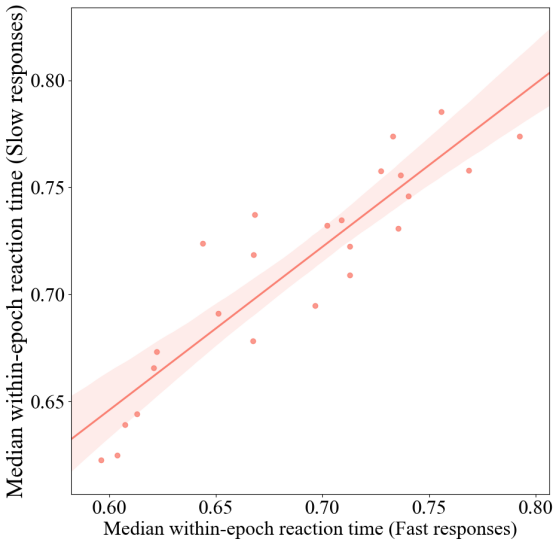
Fig. 4.6 Violin plots showing the proportion of correct responses that occur during the first 500ms of the epoch relative to correct responses that occur during the second 500ms (epochs 2-8). Scores (referred to as rapid resumption ratio) are shown for all participants in the control (CTR) and autism (ASC) groups. Dashed horizontal lines are overlaid to show the median and quartiles of each groups distribution.

Correlations of reaction times between the different trial types

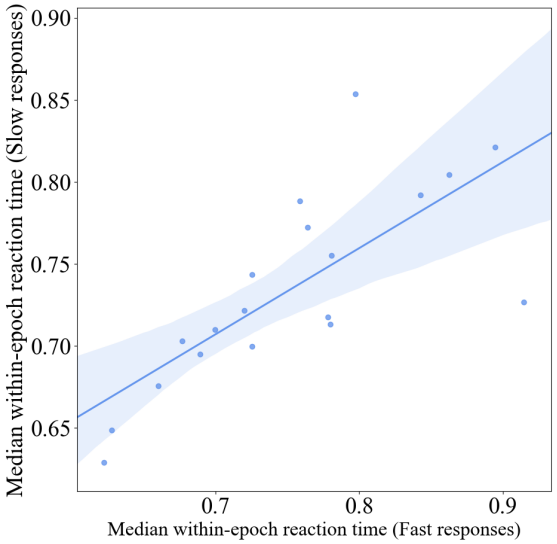
All trials in which standard responses occured were then further classified as to whether they were trials in which rapid resumption occured (trials with a within-epoch reaction time of 500ms or less) or trials in which the target was located through normal search (trials with a within-epoch reaction time of over 500ms). These trial types will be referred to as *rapid responses* and *slow responses*. These two trial types are subcategories of *standard responses*. This gives 3 types of response in total: *fast responses*, *rapid responses* and *slow responses*. Median within-epoch reaction times were then calculated for rapid and slow responses.

First, the correlation between the median within-epoch reaction times of fast responses and slow responses was examined. This was done to assess whether there was evidence to support the claim that these two response types were driven by the same, or a similar, mechanism. There was a strong and significant correlated between the measures in both the control ($r = 0.907$, $p < 0.001$) and the autism groups ($r = 0.752$, $p < 0.001$). While the strength of this correlation was slightly attenuated in the autism group, relative to the control group, this difference was not significant ($Z = 1.63$, $p = 0.103$ *two-tailed test*). Correlation plots

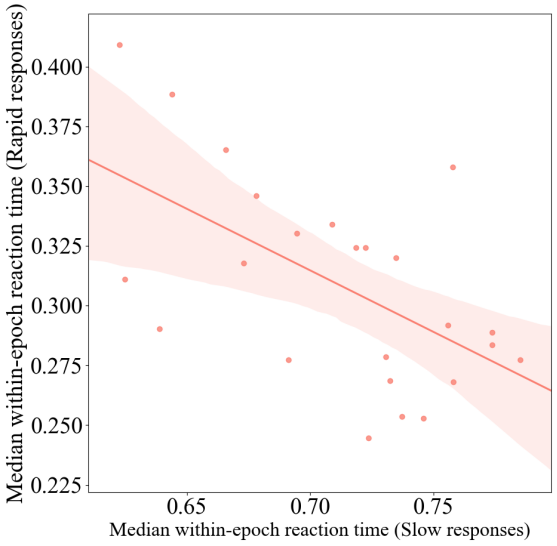
for the two groups are shown in figure 4.7 (a) and (b). Further correlation tests were carried out to assess the relationship between the two types of standard response: rapid and slow responses. A negative association was found between these two measures, which reached significance in the control group (r = -0.573, p = 0.003) but not in the autism group (r = -0.349, p = 0.143). Despite the presence of a significant relationship in one group but not the other, the difference between the strength of the correlations in the control and autism groups was not significant (Z = -0.88, $p > 0.3$ *two-tailed test*). Correlation plots for the two groups are shown in figure 4.7 (c) and (d). This suggests that control participants displayed a tradeoff between speed of response when rapid resumption occurred and speed of response when rapid resumption did not occur. While this relationship was not found to be significant in the autistic participants, there was also no evidence to suggest that they significantly differed from control participants in their association between slow and rapid responses. Therefore, it is not clear whether the non-significant correlation found in the autism group is a true difference or if the result was underpowered. Alternative, it is also possible that the result in the control group could be a false-positive.



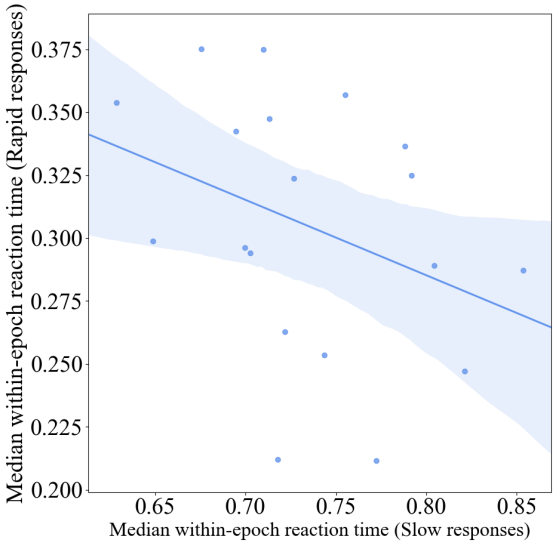
(a) Median within-epoch reaction times plotted for slow responses against fast responses in the control group.



(b) Median within-epoch reaction times plotted for slow responses against fast responses in the autism group.



(c) Median within-epoch reaction times plotted for rapid responses against slow responses in the control group.



(d) Median within-epoch reaction times plotted for rapid responses against slow responses in the autism group.

Fig. 4.7 Correlations between reaction times in the different response types. The relationship between fast responses and slow responses are shown for control (a) and autistic (b) participants. The relationship between slow responses and rapid responses are shown for control (a) and autistic (b) participants. Solid lines indicate the lines of best fit and shaded regions show the standard errors.

Effects of motor reaction times on rapid resumption

To assess whether basic motor reaction times were associated with the extent to which participants were influenced by prior information during visual search, Pearson correlation tests were conducted between median reaction times in the non-distractor control task and the RR-Basic scores from the main task. This was carried out separately for the two groups to assess whether the relationship between these variables differed between the two populations. While the direction of association differed between the groups, neither the correlation in the control group (r = -0.166, $p > 0.3$) or in the autism group (r = 0.427, p = 0.060) reached significance. These two correlations are shown in figure 4.8.

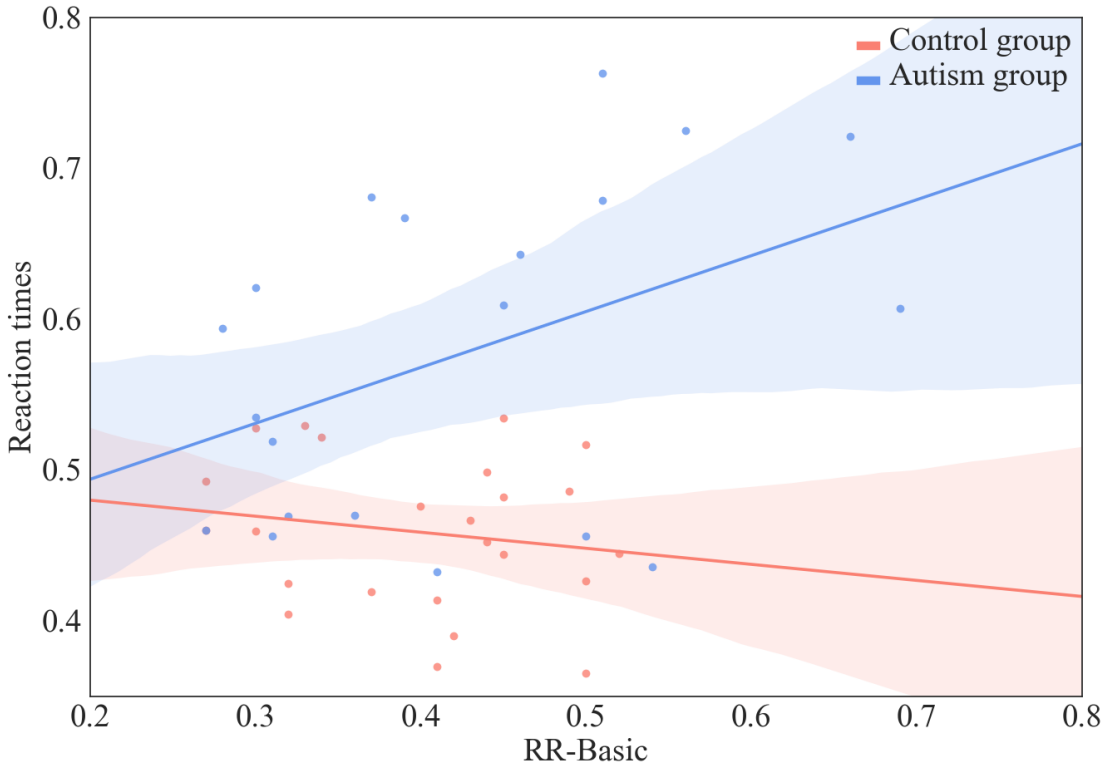
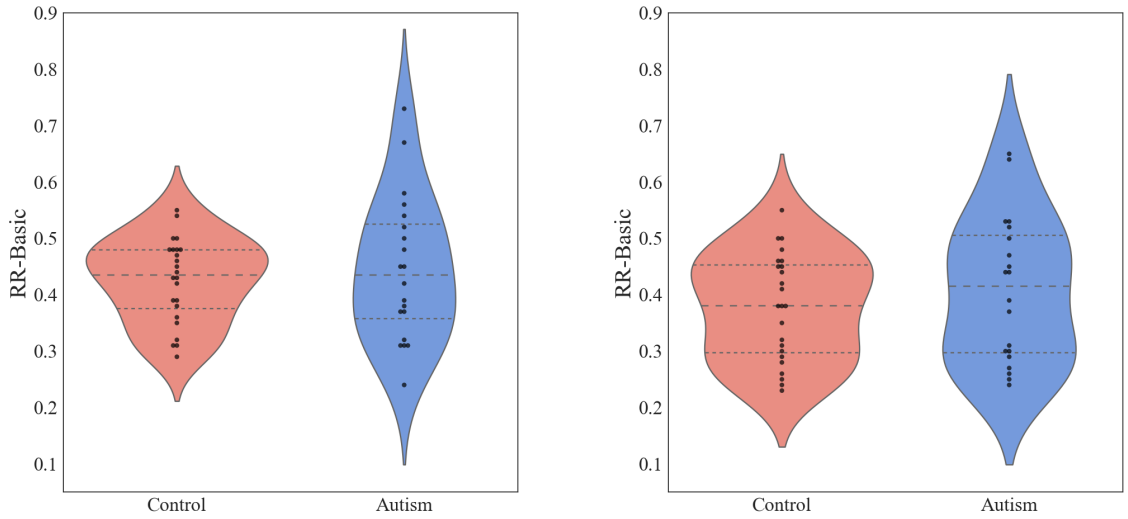


Fig. 4.8 Correlations between median reaction times in the control task and RR-Basic scores from the main task. Lines of best fit are shown and shaded regions display the standard error for the fit. Data are shown separately for autism and control groups.

Effects of distractor density on rapid resumption

It was shown in chapter 3 that there were no between-group differences for the effects of distractor density on either reaction times or error rates, as the interaction terms between

group and condition were non-significant for both the reaction time and error rate analyses. However, distractor density may have an effect on the way in which prior information is used during visual search and the nature of this effect could potentially vary between the two groups. Therefore, RR-Basic was calculated separately for low- and high-distractor conditions for each participant and the effects of distractor density on RR-Basic were assessed across the two groups.



(a) Low distractor condition

(b) High distractor condition

Fig. 4.9 Violin plots showing the RR-Basic scores for low distractor density trials (a) and high distractor density trials (b). Individual data points show the RR-Basic scores for all participants in the two groups. Dashed horizontal lines are overlaid to show the median, upper quartile and lower quartile of each groups distribution.

A 2x2 ANOVA was conducted with RR-Basic as the dependent variable, condition (low distractor vs high distractor) as a within-subject factor and group (control vs autism) as a between-subjects factor. The ANOVA found that, as demonstrated previously, there was no significant effect of diagnostic status (group) on RR-Basic scores ($F_{(1,84)} = 1.118$, $p = 0.29$). While RR-Basic scores were higher in the low distractor condition than in the high distractor condition, the effect failed to reach significance ($F_{(1,84)} = 3.487$, $p = 0.065$). The interaction between group x condition was also non-significant ($F_{(1,84)} = 0.040$, $p > 0.3$). Results from the ANOVA are summarised in table 4.2. The distributions of scores for both groups across the two conditions are shown as violin plots in figure 4.9.

	sum_sq	df	F	PR(>F)
Group	0.012742	1.0	1.118068	0.293366
Condition	0.039738	1.0	3.486717	0.065351
Group*Condition	0.000458	1.0	0.040216	0.841544
Residual	0.957333	84.0		

Table 4.2 Results from the 2x2 ANOVA with RR-Basic as the dependent variable and distractor condition (within-subjects) and group (between-subjects) as the two independent variables.

4.4 Discussion

In this chapter, I looked at the effects of prior expectations on visual search performance by grouping and contrasting different response types. I started by comparing fast responses, responses which occured after a single presentation of the search display, with standard responses, responses which occured after subsequent presentations, for both the control and autism groups. The results suggested that, for both groups, the distributions of the fast and standard responses differed significantly from each other. This suggests that the phenomenon of rapid resumption is present in both the control group and the autism group. No differences were found between the control and autism groups for standard responses but the distributions of fast responses were found to significantly differ between the two groups. While the results suggest that the two groups performed similarly when producing standard responses, this approach is not particularly sensitive to differences due to the fact that the data for the two groups were pooled across all participants. To further investigate the extent of the effect of rapid resumption across all participants, additional analyses were carried out.

To assess the rate at which participants were able to identify the target after a single presentation of the search display, I calculated the relative proportion of fast to standard responses for all participants. The average proportion of fast trials did not differ significantly between the two groups, suggesting that the autistic participants were able to immediately identify the search target to the same extent as the control participants despite their slower baseline reaction times. It is important to note that the average calculated values for the proportion of fast responses in the present study were considerably lower than the results previously reported in other studies using the interrupted search paradigm (Lleras et al., 2005, 2007). This may be due to the fact that these other studies specifically recruited undergraduate students to complete their task. As the participants included in the present study were recruited from a wider population than just undergraduate students, this sample had a greater average age than these other studies. This may explain the reduced average

proportion of fast responses in the present sample, as age is associated with slower reaction times (Wolkorte et al., 2014; Woods et al., 2015).

Baseline motor reaction times, as measured in the control task, were found to correlate with the proportion of fast responses in the autism group. However, this result did not extend to the control group. This finding was supported further by the presence of a significant interaction term between diagnostic status and the proportion of fast responses when predicting baseline motor reaction times. This result could be due to the fact that the autism group had slower reaction times on average, which may have meant that autistic participants with slower baseline reaction times were less likely to have been able to react to targets within the first epoch even if they identified the target. The limiting effect of slower reaction times on fast responses may have driven this correlation in the autism group, but would not have been present in controls due to their higher baseline reaction times.

The relationship between fast and standard responses was also considered. Error rates in fast and standard response were found to be correlated in the control group. This indicates that participants would have used similar confidence thresholds before responding in the two response types and suggests that fast responses were not simply responses in which participants guessed or responded with lower confidence. While this correlation was not found in the autism group, the difference between the associations in the autism and control groups was not significant. Therefore, it is not clear whether there was a true absence of association in the autism group or if the analysis did not have sufficient power to detect the effect. Within-epoch reaction times in fast and standard responses were not correlated in either group. This lack of correlation between reaction times in the two response types suggests that different mechanisms would have been used to generate responses of each type (Prinzmetal et al., 2005; Stafford and Gurney, 2004). This could be due to the existence of two distinct subtypes of responses within the standard responses and the effects of rapid resumption. It is worth noting, however, that the results in this analysis were conducted with fewer participants than the rest of the analyses in this chapter. This was due to the exclusion of participants that did not have a sufficient number of fast trials to be included in this analysis and could have led to some of the analyses not having the required statistical power to detect modest effects.

Using the subclassifications of the standard responses into rapid responses and slow responses, I explored the relationship of each of these two response types with fast responses in order to better understand the underlying mechanisms generating these responses. I found evidence to suggest that similar mechanisms were involved during slow and fast responses, based on strong positive correlations between the within-epoch reaction times for these two types of response (Dean et al., 2011; Hedge et al., 2018). I also found evidence of a potential

tradeoff between within-epoch reaction times in rapid responses and within-epoch reaction times in slow responses for the control group, based on a negative correlation between these two measures. This could be due to a reliance on prior information negatively affecting responses where rapid resumption didn't occur and prior information wasn't utilised. While this correlation was non-significant in the autism group, the difference between the correlations in the two groups did not differ significantly. However, the magnitudes of the correlations did vary across the two groups despite the difference being non-significant. A weak correlation was found between these measures in the autism group and a moderate/strong relationship was found in the control group. The correct interpretation of these results is not entirely clear here but it may be case that the effect observed in the control group, that a reliance on prior information negatively affects responses in which prior information isn't able to be utilised, is attenuated in the autism group. Were it possible to replicate the present study and find stronger evidence for this potential difference, it could be seen as evidence of autistic individuals being affected by the influence of prior information to a lesser degree. However, as the present results were unable to find a significant difference between the two correlations, this possibility will not be discussed here further. Finally, the effects of motor reaction time and distractor density on the proportion of rapid responses were also considered. Neither measure significantly influenced RR-Basic scores, indicating that there was no evidence to suggest that the extent to which individuals use prior information during search was influenced by either their baseline reaction times or the difficulty of the task.

There were some limitations to the methods used in the present chapter, particularly in the use of the RR-Basic metric to quantify the degree to which prior information was used by participants. The method suggested by Lleras et al. (2011a) was based on their operational definition of rapid resumption (Lleras et al., 2005, 2007) and therefore does not have strong empirical evidence to support it. As their method of classification is binary and based solely on a reaction time cutoff, the method may be overly simplistic. This could result in aspects of performance not being captured by the approach. These concerns will be addressed comprehensively in the following chapter. The results in the present chapter appear to provide evidence which suggests that autistic individuals show intact use of prior information to facilitate visual search. However, as the following chapter will focus on verifying and expanding the methods used in the present chapter, I will postpone any further interpretation of the potential findings reported here until the full set of results have been obtained and presented.

Chapter 5

Classification of trial types during interrupted visual search

Overview

In this chapter, I aimed to verify the result from the previous chapter which suggested that autistic individuals showed intact use of prior information during an interrupted search task. This was done using a data-driven approach to classify the different trial types by modelling participant response distributions as Gaussian mixture models.

5.1 Background

It is common that distributions of responses which are obtained from single-condition behavioural tasks (tasks in which the behavioural paradigm is consistent across all trials) are assumed to be a result of a single underlying cognitive process. However, there may be cases in which two distinct processes are used during a single-condition task. Distinct cognitive processes are more often seen in multiple-condition tasks where two types of condition are presented to participants. One such example of this is the Posner cueing task, in which trials may either have valid or invalid cues (Posner, 1980). In tasks such as this, data are normally stratified by the type of task condition to allow for statistical comparison. This is straightforward in multiple-condition tasks where the different response types occur as a direct result of task manipulation. However, a different approach is required in the case

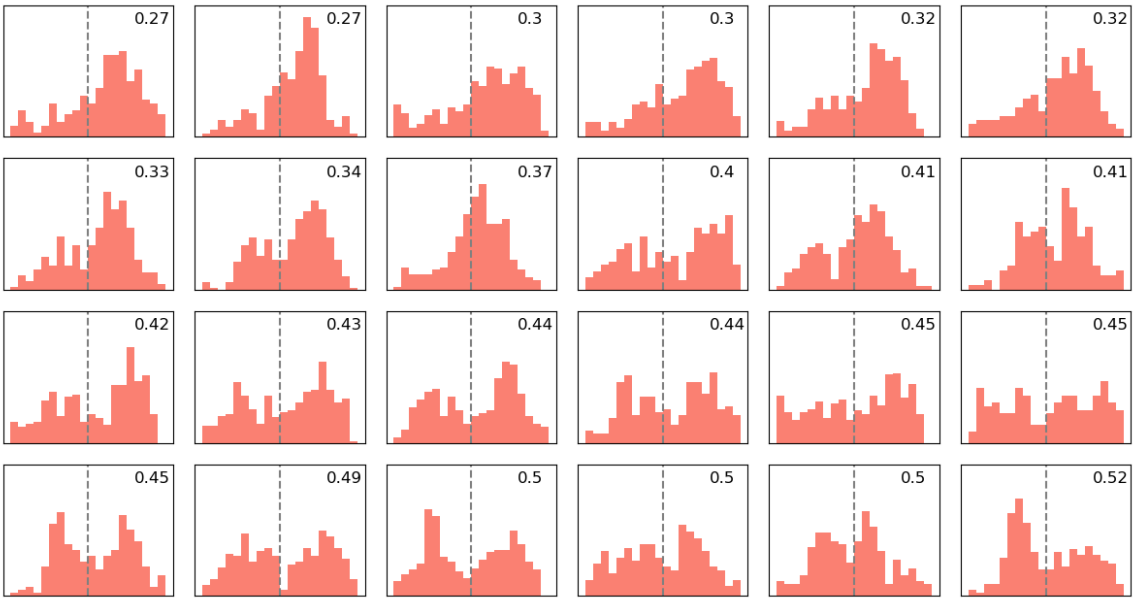
of single-condition tasks, such as the present search task, as different response types occur throughout the task independently of any task manipulation. This means there are no directly observable labels that indicate which response type occurred in any given trial.

In the previous chapter, I examined how prior exposure to a search display affected visual search performance and whether there were differences between autistic and non-autistic individuals in the extent of this effect. The degree to which prior exposure to the search display affects responses can be gauged by determining the relative proportion of trials in which rapid resumption is thought to occur. The approach I used to assess this effect in the previous chapter was based on the methods used and reported by Lleras et al. (2011a), the same researchers that originally reported the phenomenon of rapid resumption (Lleras et al., 2005). They classified trials where rapid resumption was thought to have occured using a cut off value of 500ms, which was based on their operational definition of rapid resumption. This allowed for a comparison to be made between the reaction time distributions of the two different response types and for the relative proportion of each response type to be calculated. Using this method, the results suggested that autistic and non-autistic participants did not differ in the extent to which they were influenced by prior exposures to the search display.

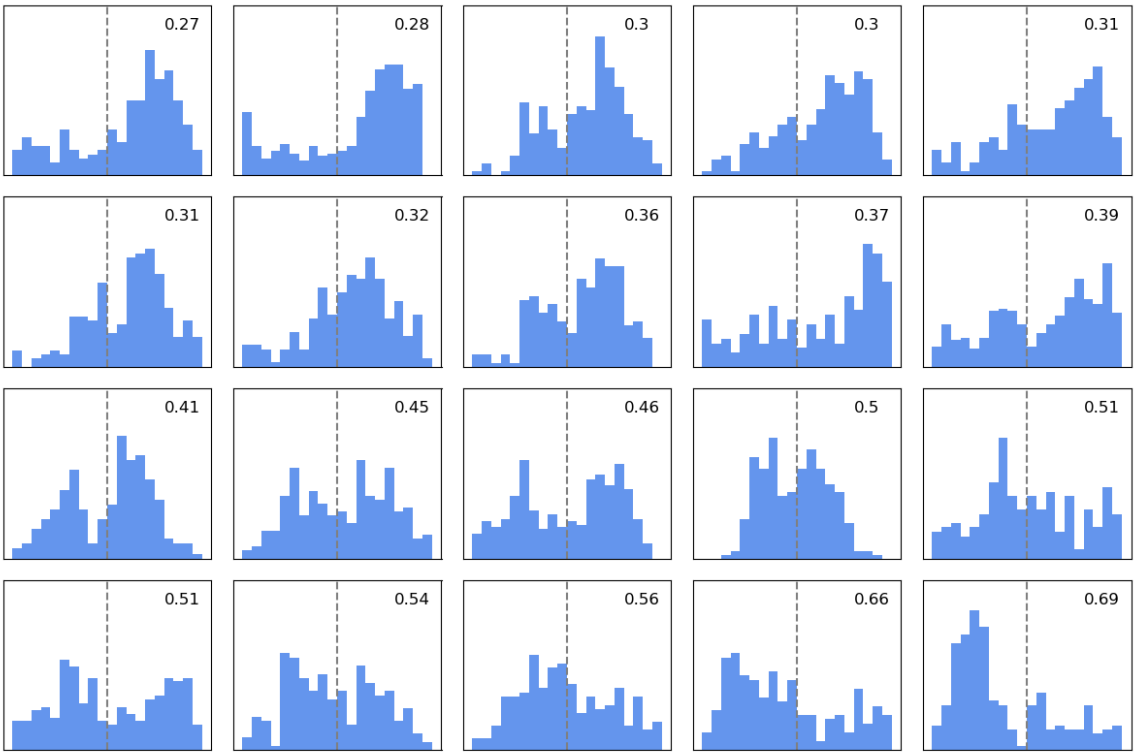
5.1.1 Suitability of previous methodology

The method developed by Lleras et al. (2011a), and used in the previous chapter, has some potential issues regarding its validity and suitability for classifying response types in the interrupted search paradigm. Firstly, the defined cutoff used to differentiate between response types is slightly arbitrary as it wasn't derived empirically from behavioural data. The cutoff used in this approach was chosen primarily based on visual inspection of data (Lleras et al., 2005, 2007) and is therefore unlikely to allow for optimal labelling of the different response types. By using more sophisticated statistical methods, empirical data can be used to classify response types more accurately.

The second concern with this approach is that the classification approach used is binary and so it may lose some of the richness of the response data. Scoring participants on the relative proportion of these binary response types might not fully capture the variability in performance across participants. This can be seen when individual participant distributions are plotted, as shown in figure 5.1. It is clear that in some cases there is a large amount of variation in the characteristics of response distributions between participants that were calculated as having similar RR-Basic scores.



(a) Control participants



(b) Autistic participants

Fig. 5.1 Response distributions shown for all participants in the control group (a) and autism group (b). The values in the top-right corner of each plot show the basic rapid resumption ratio (RR-Basic) calculated for each participant. The t_{epoch} = 0.5s threshold, which indicates the cutoff for classifying trials as rapid or slow, is shown on all plots as a dotted line.

5.1.2 Simulation of problematic data

To further illustrate the potential variance in performance that the RR-Basic scores fail to capture, I generated simulated data for 3 different hypothetical response distributions (see figure 5.2). These 3 response distributions were created using distinct underlying generative models. Distributions (a) and (c) were each drawn from single Gaussians. While both of these had a mean reaction time of $\mu = 0.5$, they had differing variances of $\sigma = 0.07$ and $\sigma = 0.3$ respectively. Distribution (b) was drawn from a mixture of two Gaussians with the same variance ($\sigma = 0.1$) but different means ($\mu = 0.25$ and $\mu = 0.75$). Using the approach used by Lleras et al. (2011a) to classify these different distributions (in terms of the proportion of rapid resumption responses that they contain) gives us the same value (RR-Basic = 0.5) for all 3 distributions. As we know they have distinct underlying generative models, this result highlights how the RR-Basic measure fails to capture certain types of variation in response distributions that may be indicative of differences in performance on the task. Developing an alternative approach which is more sensitive to these potential differences in the underlying response distributions may allow for better detection of individual differences in the extent to which participants are influenced by prior information during visual search.

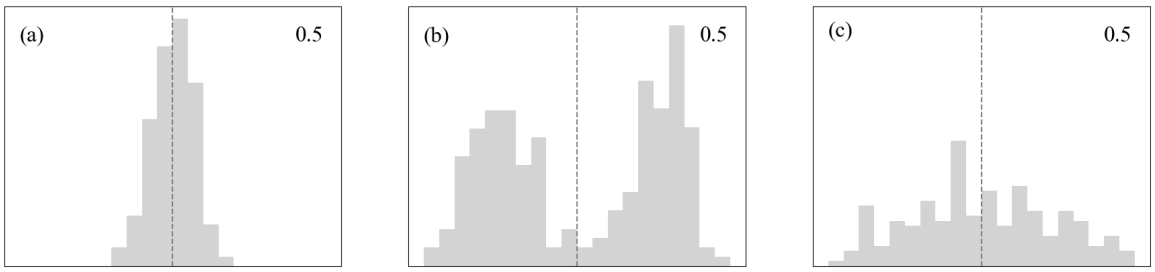


Fig. 5.2 Simulated reaction time distributions. Distribution (a) was drawn from a single Gaussian of $\mu = 0.5$ and $\sigma = 0.07$. Distribution (b) was drawn equally ($\lambda = 0.5$) from a mixture of two Gaussians with the same variance ($\sigma = 0.1$) but different means ($\mu = 0.25$ and $\mu = 0.75$). Distribution (c) was drawn from a single Gaussian of $\mu = 0.5$ and $\sigma = 0.3$.

5.1.3 Alternative approach to classifying response types

When considering the data obtained from the interrupted search task (excluding fast responses), we can view the overall distribution of responses as being comprised of two separate distributions. When distributions are derived from two or more distinct models, we can capture the underlying probabilistic structure using mixture modeling (Bishop, 2006). Based on the evidence put forward by Lleras and colleagues (Lleras et al., 2005, 2007) there is a strong reason to believe that there are two distinct response types that occur within the

interrupted search paradigm, these being (i) those responses which involve rapid resumption and (ii) responses which don't involve rapid resumption.

In terms of the true underlying cognitive mechanisms responsible for the different response types, there is no direct way of observing which response type occured in any given trial. Therefore, we can describe the response type as a *latent variable* (or a *hidden variable*), a variable which is not directly observable but can be inferred from other observed variables. The main observed variable that we can use in the present study is reaction time. The method used by Lleras et al. (2011a) was essentially a way of using a simple classification rule to infer the latent variable, response type, from the observed variable, reaction time. The main concern with this approach, as outlined earlier, is the suitability of the classification rule used to infer the latent variable from the observed data. Before concluding that the behavioural results obtained in the previous chapter were valid, and did provide satisfactory evidence of intact use of prior information during visual search in autistic individuals, I will use a data driven approach to develop a novel method of using reaction times from trials to infer the most likely response type for any given trial. This method will be evaluated and compared with the results from the method used by Lleras et al. (2011a), before concluding whether there is sufficient evidence to support the results reported in the previous chapter.

This alternative approach to estimating the latent variable from the observed data will be based on extracting the parameters for the separate unimodal distributions of the different response types and then using these parameters to calculate which distribution was more likely to have generated each individual response. The outline of this approach is shown in figure 5.3. The overall response distribution for the combined distributions is assumed to be a bimodal distribution, as illustrated by diagram 5.3 (a). The first step is to estimate the distribution parameters of the two individual Gaussian distributions that would generate similar data to the observed bimodal distribution. This step is shown in diagram 5.3 (b). Once these parameters have been estimated, individual data points can be assessed to determine which of the two Gaussians they were more likely to have been generated by. Two example data points, x_i and x_j, are shown in diagram 5.3 (c). Both of these example data points are more likely to have been generated by the rightmost Gaussian distribution, as indicated in diagram 5.3 (d). The additional advantage of the new approach is that the likelihood to which these data points are expected to have been generated by a given distribution and not the other can also be quantified. In this instance, x_j will be more likely to have been generated by the highlighted Gaussian than x_i. The exact details and methodology of approach will be outlined in greater detail below.

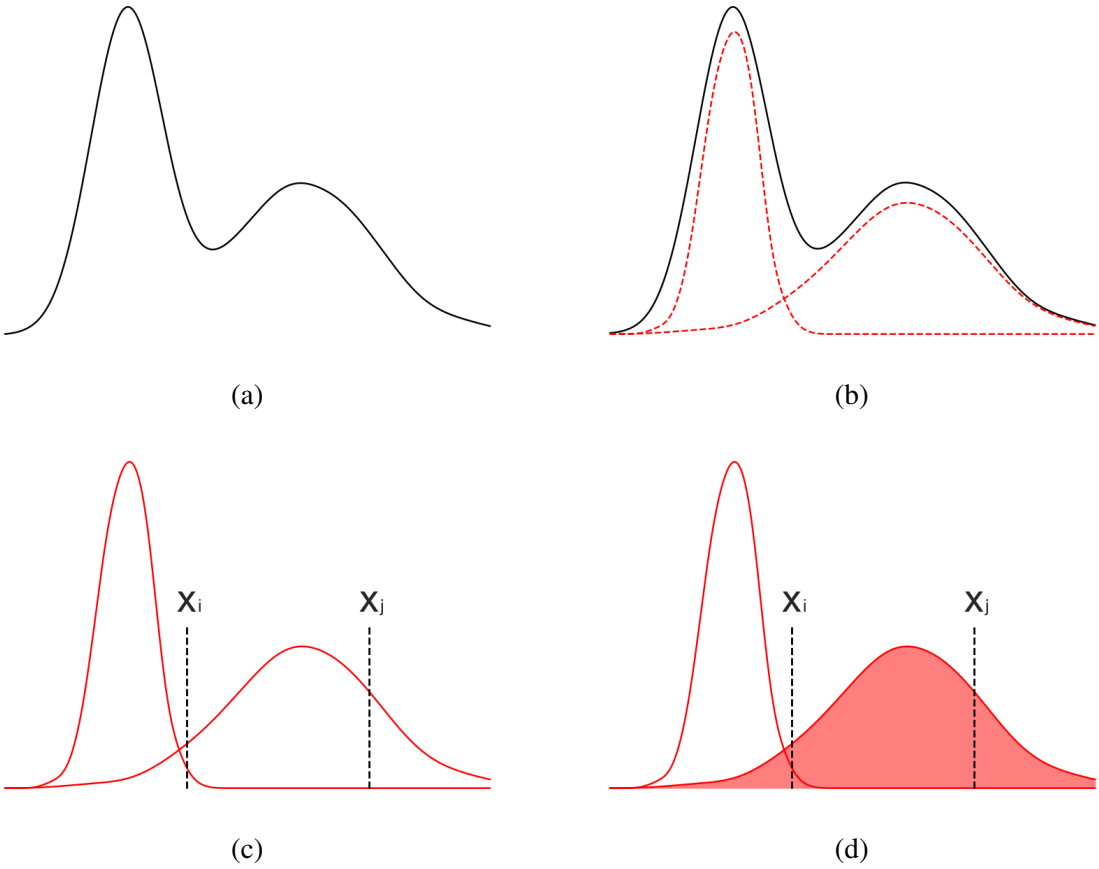


Fig. 5.3 Demonstration of the procedure used to classify data generated by a bimodal distribution. Diagram (a) shows a hypothetical binomial distribution. A Gaussian mixture model can be used to estimate the parameters of the different components of the binomial distribution as shown in diagram (b). These can be used to label data points such as x_i and x_j based on which distribution they were most likely to have been drawn from, as shown in diagrams (c) and (d).

5.2 Methods

For the present analysis, only participant responses that occured following subsequent presentations of the search display (standard responses) were included. The approach taken here rests on the assumption that these responses were generated by one of two distinct underlying processes. These different response types are labeled as either rapid responses or slow responses. As these response types were not directly observable, responses were considered to have a latent variable that labelled which process generated the given response. The general approach taken here was to treat the full set of standard responses as a mixture model consisting of two distinct Gaussian distributions which capture the underlying characteristics of rapid responses and slow responses. The underlying parameters of the two model components will be estimated using a modelling approach on the pooled participant data. This model will then be used to infer the latent variable (response type) using the observed data (reaction time) for all participant responses.

5.2.1 Gaussian mixture models

One example of a latent variable model is the Gaussian mixture model. A mixture model is an example of a hidden model, in which observations are generated from a mixture of two distinct generative models. A Gaussian mixture model is a common example of this, which consists of a mixture model comprising of two or more Gaussian distributions. Gaussian mixture models are suitable for the present study, in which I want to calculate whether trials should be classified as rapid resumption responses. The Gaussian distribution can be expressed as:

$$\mathcal{N}(x|\mu,\sigma) = \frac{1}{\sigma(2\pi)^{1/2}} \exp - \left(\frac{(x-\mu)^2}{\sigma^2} \right) \tag{5.1}$$

Where μ is the expected value of the data set x and σ^2 is the variance of the data set. We can define a mixture model as such:

$$p(x|\{\theta_k\}) = \sum_{k=1}^{K} \lambda_k p_k(x|\theta_k) \tag{5.2}$$

Here λ_k represents the relative weights of the different components (for a model with k components) where $\sum \lambda_k = 1$ and $p_k(x|\theta_k)$ represents the respective components of the subpopulations with θ_k referring to the parameter set for component k. Note that this assumes that $\lambda_k > 0$ for all values of k, otherwise the model contains non-contributive subpopulations

which can be ignored. Gaussian mixture models are a specific case of mixture models in which the distributions for the subpopulations are Gaussian. This can be written as:

$$p(x|\{\theta_k\}) = \sum \lambda_k \mathcal{N}(x|\mu_k, \Sigma_k) \tag{5.3}$$

Within the mixture model, each individual Gaussian density $\mathcal{N}(x|\mu_k, \Sigma_k)$ is referred to as a component of the mixture and has specific values for its mean μ_k and covariance Σ_k. The parameters λ_k are the mixing coefficients, which are the relative weights of each distribution within the mixture model. If we integrate equation 5.3 with respect to x, while incorporating the fact that both $p(x)$ and each of the individual Gaussian components are normalized, we are given:

$$\sum_{k=1}^{K} \lambda_k = 1 \tag{5.4}$$

By definition, both $p(x) \geq 0$ and $\mathcal{N}(x|\mu_k, \Sigma_k) \geq 0$. This indicates that $\lambda_k \geq 0$ for all values of k. We can combine these statements with 5.4 to show that the mixing coefficients meet the criteria to be probabilities:

$$0 \leq \lambda_k \leq 1 \tag{5.5}$$

We can also state across all the components k that:

$$p(x) = \sum_{k=1}^{K} p(k)p(x|k) \tag{5.6}$$

So, we can see that λ_k is equivalent to $p(k)$, which is the prior probability of a data point coming from the k_{th} component. Additionally, the density $\mathcal{N}(x|\mu_k, \Sigma_k) = p(x|k)$ can be regarded as the probability of data point x given component k. The properties of the Gaussian mixture distribution are defined by the parameters λ, μ and Σ, which refer to sets containing the parameters of the individual components $\lambda \equiv \{\lambda_1, ..., \lambda_K\}$, $\mu \equiv \{\mu_1, ..., \mu_K\}$ and $\Sigma \equiv \{\Sigma_1, ..., \Sigma_K\}$.

In the present study, we have no direct information that tells us which of the two underlying processes general any given response. In order to be able to estimate which underlying process is the cause of individual responses, we need to have an idea of the specific characteristics of the distributions for the different subpopulations. In the case of a Gaussian mixture model, we need to estimate the number of subpopulations, k, the charcteristics of each Gaussian, μ_k and Σ_k, as well as the relative weight of each subpopulation distribution to the overall population, λ_k. A standard approach for estimating parameters such as these is

to find the maximum likelihood. This involves finding values of parameters for which the likelihood function is maximised. The log likelihood function can be written as:

$$\log p(X|\lambda,\mu,\Sigma) = \sum_{n=1}^{N} \log \left\{ \sum_{k=1}^{K} \lambda_k \mathcal{N}(x_n|\mu_k,\Sigma_k) \right\} \tag{5.7}$$

This equation includes a summation term within the logarithm. This leads to it not being possible to solve the derivative of this in closed-form, so we have to turn to the Expectation-Maximisation algorithm to estimate our parameter values.

5.2.2 Expectation-Maximisation algorithm

The Expectation-Maximization algorithm is an iterative method which can be used to find the maximum likelihood estimate in models that contain latent variables (Dempster et al., 1977). It works by starting with initial parameter estimates and then iterates through an *Expectation Step* and a *Maximisation Step* until the estimates for the parameters converge on a stable solution. The Expectation Step assumes the current parameter estimates are fixed and uses these to compute the expected values of the latent variables in the model. The Maximisation Step takes the expected values of the latent variables and finds updated values for the previous parameter estimates that maximise the likelihood function.

In the case of a Gaussian mixture model, the Expectation Step assumes that the values of all the 3 parameters for the Gaussians in the model are fixed and then computes the probability that each given data point is drawn from each of the individual Gaussians in the model. This property, the probability that a data point is drawn from a specific distribution, is referred to as the *responsibility* of the distribution to a given data point. Once the responsibility values are calculated, the Maximization Step assumes these responsibilities are fixed and then attempts to maximize the likelihood function across all the model parameters.

The responsibilities are equivalent to the posterior probabilities for a given component within the model and can be calculated as follows:

$$\gamma(z_k) = p(z_k = 1|x) = \frac{p(z_k = 1) \cdot p(x|z_k = 1)}{\sum_{j=1}^{K} p(z_j = 1) \cdot p(x|z_j = 1)} \tag{5.8}$$

$$= \frac{\lambda_k \cdot \mathcal{N}(x|\mu_k,\Sigma_k)}{\sum_{j=1}^{K} \lambda_j \cdot \mathcal{N}(x|\mu_j,\Sigma_j)} \tag{5.9}$$

Where $\sum_{j=1}^{K} \lambda_j \cdot \mathcal{N}(x|\mu_j,\Sigma_j)$ is the normaliser term across all components. The resposibility of a component of the model to a data point is equivalent to the normalised probability

of a given data point belonging to a specific Gaussians within the mixture model, then weighted by the estimated mixture proportions (λ_k). This is the posterior probability for a specific distribution given the observed data, x. Using this, it is possible to calculate the distribution of the prior mixture weights. The responsibilities can be summed and normalize to estimate the contribution of the individual Gaussians to the observed data:

$$\lambda_k = \frac{1}{N}\sum_i \gamma(z_k) \tag{5.10}$$

We can also use the responsibilities of each point to each distribution to estimating the mean and standard deviation of the Gaussians and then weight them based on the responsibilities:

$$\mu_k = \frac{\sum_i \gamma(z_k)x_i}{\sum_i \gamma(z_k)} \tag{5.11}$$

and

$$\sigma_k = \frac{\sum_i \gamma(z_k)(x_i-\mu_k)(x_i-\mu_k)}{\sum_i \gamma(z_k)} \tag{5.12}$$

We can see that it would be straightforward to calculate the posteriors for the components within the model if the distribution parameters were known and, similarly, it would be easy to calculate the parameters were the posterior know. The Expectation-Maximisation algorithm overcomes this issue of circularity by alternating between fixing the posterior or the parameters while maximising the likelihood. Initially, the parameters are fixed and then the posterior distribution is calculated for our hidden variables. Then, the posterior distribution is fixed and the parameters are optimised. These steps are repeated in an alternating fashion until the likelihood value converges.

5.2.3 Estimation of mixture model components

I used the Expectation-Maximisation algorithm to estimate the parameters for the individual distributions of rapid and slow responses. Once the parameters of these two distributions had been estimated, I would be able to not only reclassify all participant responses using an empirically derived criterion but also quantify the relative likelihood of each individual classification. The Expectation-Maximisation algorithm was carried out by initialising the parameters and then iterating through the Expectation and Maximisation steps until the parameters converged. The individual steps of the Expectation-Maximisation algorithm are detailed below.

I. Initialisation

The means μ_k, covariances Σ_k and mixing coefficients λ_k were initialised by using the classification method in the previous chapter (RR-Basic) to classify data points across all participants and then estimating the distributions of the two response types based on these classifications.

II. Expectation Step

The responsibilities (posteriors) for the individual components were evaluated using the current estimates for the parameter values:

$$\gamma(z_{nk}) = \frac{\lambda_k \cdot \mathcal{N}(x_n|\mu_k, \Sigma_k)}{\sum_{j=1}^{K} \lambda_j \cdot \mathcal{N}(x_n|\mu_j, \Sigma_j)} \tag{5.13}$$

III. Maximisation Step

The parameters were then updated by re-estimating them based on the current values for the responsibilities:

$$\mu_k^{new} = \frac{1}{N_k} \cdot \sum_{n=1}^{N} \gamma(z_{nk}) \cdot x_n \tag{5.14}$$

$$\Sigma_k^{new} = \frac{1}{N_k} \sum_{n=1}^{N} \gamma(z_{nk}) \cdot (x_n - \mu_k) \cdot (x_n - \mu_k)^T \tag{5.15}$$

$$\lambda_k^{new} = \frac{N_k}{N} \tag{5.16}$$

where:

$$N_k = \sum_{n=1}^{N} \cdot \gamma(z_{nk}) \tag{5.17}$$

IV. Convergence criteria

Convergence was checked for both the model parameters and log likelihood. The convergence criteria were all set as 10^{-15}. During each iteration of the Expectation-Maximisation algorithm, the updates parameter and log likelihood estimates were compared to the previous estimates to assess whether the change in values met the convergence criteria. The log likelihood was estimated as follows:

$$\log p(X|\mu,\Sigma,\lambda) = \sum_{n=1}^{N} \log \left\{ \sum_{k=1}^{K} \lambda_k \mathcal{N}(x_n|\mu_k,\Sigma_k) \right\} \tag{5.18}$$

If any of the parameters or the log likelihood satisfied the convergence criteria then the algorithm terminated, otherwise the next iteration was started.

5.2.4 Log probability ratio

Once these parameters for the distributions of rapid and slow responses had been estimated, log probability ratios were calculated for all trials across each participant individually. The log probability ratios could be used to classify responses as either rapid or slow which in turn allowed for an updated calculation of the ratio of rapid to slow responses for all participants. This updated measure will be referred to as RR-Model which can then be compared to the RR-Basic scores that were calculated in the previous chapter. Additionally, the log probability ratios allow for a measure of the cumulative confidence of classifications to be calculated for individual participants. For the current dataset, the set of latent variables (which refer to the components of the Gaussian mixture model) is $Z \equiv \{z_R, z_S\}$ where z_R and z_S are multinominal vectors such that $z_R = 1$ is a classification of a rapid response and $z_S = 1$ is a classification of a slow response. For any given response x_i we can forumlate the probabilities of the observed responses either being classified as a rapid response or a slow response. These can be written respectively as:

$$P(z_R = 1 \mid x) = \frac{P(x \mid z_R = 1)\, P(z_R = 1)}{P(x)} \tag{5.19}$$

and

$$P(z_S = 1 \mid x) = \frac{P(x \mid z_S = 1)\, P(z_S = 1)}{P(x)} \tag{5.20}$$

As a binary classification (two classes) has been used and slow trials are defined as any trials in which rapid resumption has not occurred, we can also state that:

$$P(z_R = 1 \mid x) + P(z_S = 1 \mid x) = 1 \tag{5.21}$$

We can then combine equations 5.19 and 5.20 with 5.21. This gives us an equation for the normaliser term $P(x)$:

$$P(x \mid z_R = 1)P(z_R = 1) + P(x \mid z_S = 1)P(z_S = 1) = P(x) \tag{5.22}$$

This can be rearranged to give the probability that data point x will be classified as a rapid response:

$$P(z_R = 1 \mid x) = \frac{1}{\frac{P(x|z_S=1)P(z_S=1)}{P(x|z_R=1)P(z_R=1)} + 1} \tag{5.23}$$

All the terms within this equation are computable from the observed data. The prior probabilities $P(z_R = 1)$ and $P(z_R = 1)$ can be estimated from the observed data. We can calculate the posterior terms $P(x|z_R = 1)$ and $P(x|z_S = 1)$ by assuming that:

$$P(x \mid z_k = 1) = \mathcal{N}(x \mid \mu_k, \sigma_k^2) \tag{5.24}$$

where $z_k = 1$ is the response type (either rapid, $z_R = 1$, or slow, $z_S = 1$) and μ_k and σ_k^2 are the estimates for the mean and standard deviation of the given response distribution which were calculated using the Expectation-Maximisation algorithm. From this it is possible to calculate the log probability ratio, the ratio of log likelihood probabilities for the Gaussian components of the model.

$$\log \frac{P(z_R = 1|x)}{P(z_S = 1|x)} = -\frac{1}{2}\left(\frac{(x-\mu_r)^2}{\sigma_r^2} - \frac{(x-\mu_s)^2}{\sigma_s^2} + \log \sigma_r^2 - \log \sigma_s^2\right) + \log P(z_R = 1) - \log P(z_S = 1) \tag{5.25}$$

The final form shows the 3 mains components of the log probability ratio: the variance-weighted Euclidean distances from the means ($\frac{(x-\mu_r)^2}{\sigma_r^2} - \frac{(x-\mu_s)^2}{\sigma_s^2}$), the log variances ($\log \sigma_r^2 - \log \sigma_s^2$) and the difference in log prior probabilities ($\log P(\omega_r) - \log P(\omega_s)$). A log probability ratio of 0 would suggest that the observed response was equally likely to have been generated by either distribution, with positive values suggesting stronger evidence that the response was a rapid resumption trial and negative values suggesting that the observed trial was a standard response. These values can be accumulated across all responses for each individual participant using sequential Bayesian updating. This approach rests on the assumption that the outcome on the n^{th} trial is independent of the outcome on the $n-1^{th}$ trial. To verify whether this assumption holds, regression can be used to assess whether previous trial response type has an effect on current trial response type. Additionally, it is worth considering that the accumulation of *directional* log probability ratios is not entirely informative as distributions which are evenly balanced across the classification boundary will have values close to zero regardless of the likelihood of the individual trial classifications. Returning to the simulated distributions in figure 5.2, accumulation of the direction log probability ratios would still not be able to differentiate between these 3 distributions. Therefore, the absolute values of the log probability ratio for each individual trial should be considered. These absolute values

of the log probability ratios can be accumulated across both response types combined, to give an overall measure of classification confidence for each participant, or for each of the response types individually, to create 2 distinct within-subjects measures.

5.3 Results

5.3.1 Parameter estimation of response distributions

The Expectation-Maximisation algorithm was initilialised using the values detailed in the methods section. The algorithm found a two-Gaussian fit for the response distribution. As no differences were found between the distributions for standard responses between the two groups, parameter estimation was carried out on data from all participants. The parameters for the two Gaussians were $\mu_a = 0.32$, $\sigma_a = 0.16$ and $\mu_b = 0.74$, $\sigma_b = 0.12$ with a λ of 0.54. To ensure the parameter estimates were accurate, the Expectation-Maximisation algorithm was run 100 times. The algorithm consistently converged on the same values with an average of 599.5 iterations (SD = 33.1) taken to converge. The fit of the estimated Gaussians to the observed data is shown in figure 5.4. To contrast these parameters with the Lleras et al. (2011a) method used in the previous chapter, the threshold value between the two response type classifications was calculated. This value represents the exact within-epoch reaction time for which faster responses would be classified as rapid responses and slower responses would be classified as slow responses. This is calculating by using the model parameters and finding the reaction time for which the log probability ratio is minimized. The calculated threshold reaction time was 448ms, which indicates that the difference between the value used by Lleras et al. (2011a) and the empirically derived value estimate by the model is a modest 52ms. This suggests that the cutoff used by Lleras and colleagues was a good estimate and supports the validity of the methods used in the previous chapter. Despite the small difference, this model will be used to recalculate the proportion of rapid to slow responses to allow for the new measure (RR-Model) to be statistically compared to the old measure (RR-Basic).

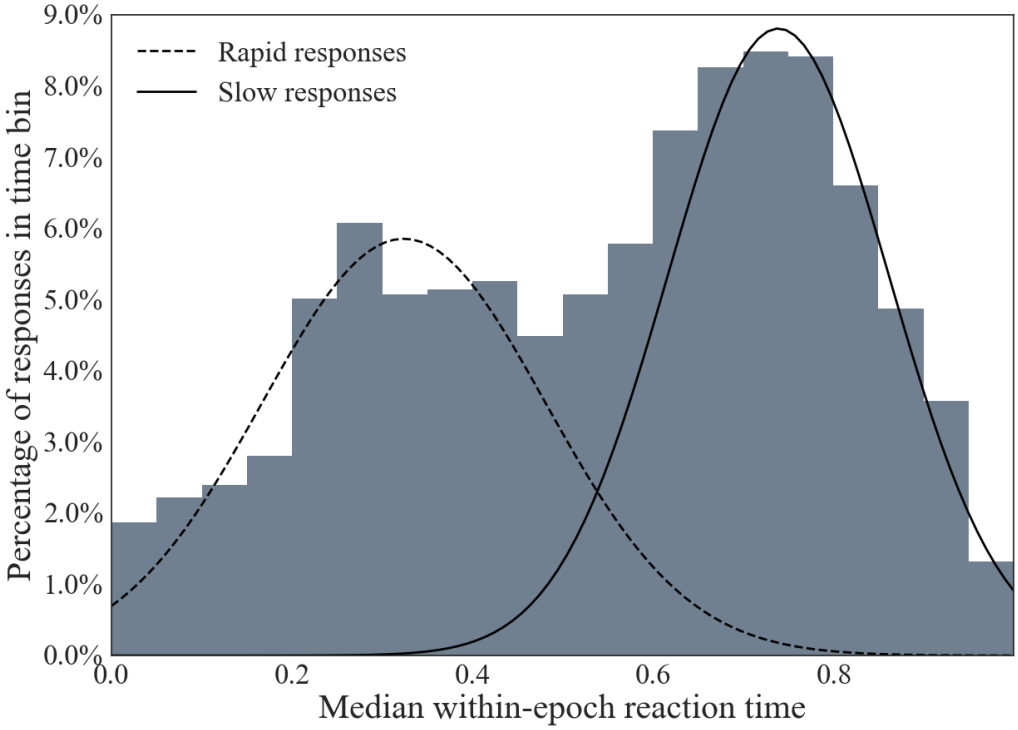


Fig. 5.4 Histogram showing the percentage of responses within different time bins for standard responses. Data shown for all responses pooled across participants. The two curves show the estimated distributions from the Gaussian mixture model. The Gaussian for rapid responses is shown as a dashed line and the Gaussian for slow responses is shown as the solid line.

5.3.2 Reclassification of rapid responses

Participant data was then modelled using these estimated parameters. For each trial, a classification likelihood value was calculated using the median within-epoch reaction time and the estimated parameters for the underlying Gaussians obtained using the Expectation-Maximisation algorithm. The log probability ratio was calculated for all responses and was used to classify the response type for each individual trial. Trials with positive log probability ratios were classified as rapid responses and trials with negative log probability ratios were classified as slow responses. No trials were calculated as having a log probability ratio of exactly 0 and so there were no ambiguous cases.

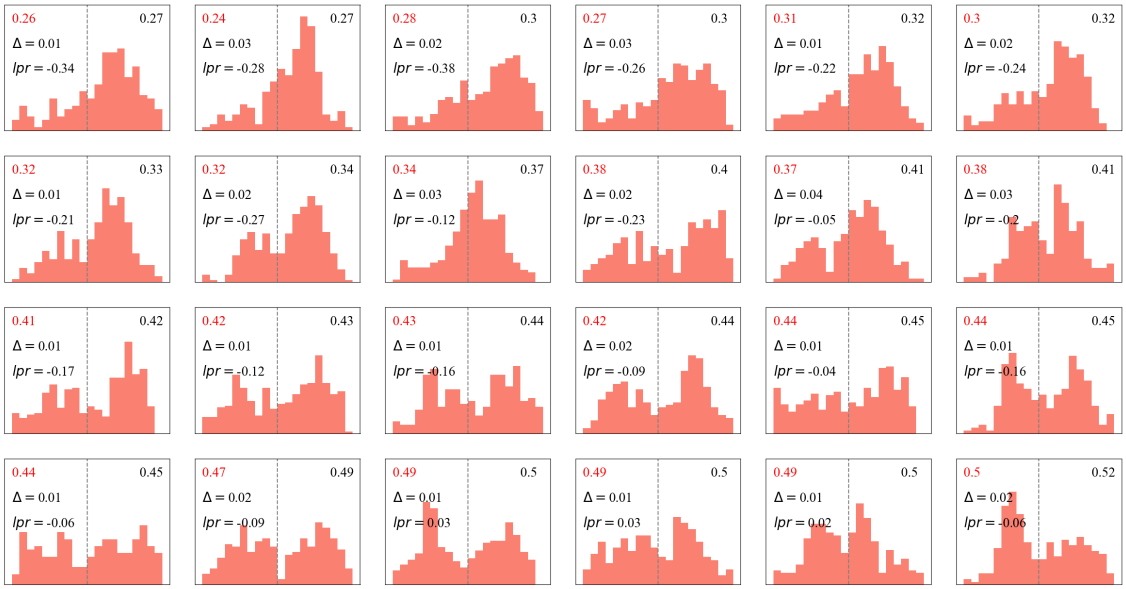
The new classifications were used to calculated an updated rapid resumption ratios, which will be referred to as the RR-Model scores. Figure 5.5 shows the response distributions for all participants, with both the RR-Model scores (top-left corner in red) and the RR-Basic scores (top-right corner). The difference between the RR-Model scores and the RR-Basic scores were calculated by subtracting the former from the later. These difference scores (Δ) are shown for each participants response distribution along with the calculated log probability ratio (lpr). The calculated RR-Model values were compared to the RR-Basic values to assess whether the modelling approach yielded significantly different estimates than the approach used by Lleras et al. (2011a).

A 2-factor analysis of variance were conducted, with method of calculation (RR-Basic v RR-Model) as a within-subject measure, group (autism v control) as a between-subjects measure and the calculated rapid resumption ratio values as the outcome variable. The results from the ANOVAs are shown in tables 5.1. The effects for diagnosis ($F_{(1,84)} = 1.12$, $p = 0.29$), method ($F_{(1,84)} = 0.64$, $p > 0.3$) and the interaction of group x method ($F_{(1,84)} = 0.00$, $p > 0.3$) were all non-significant.

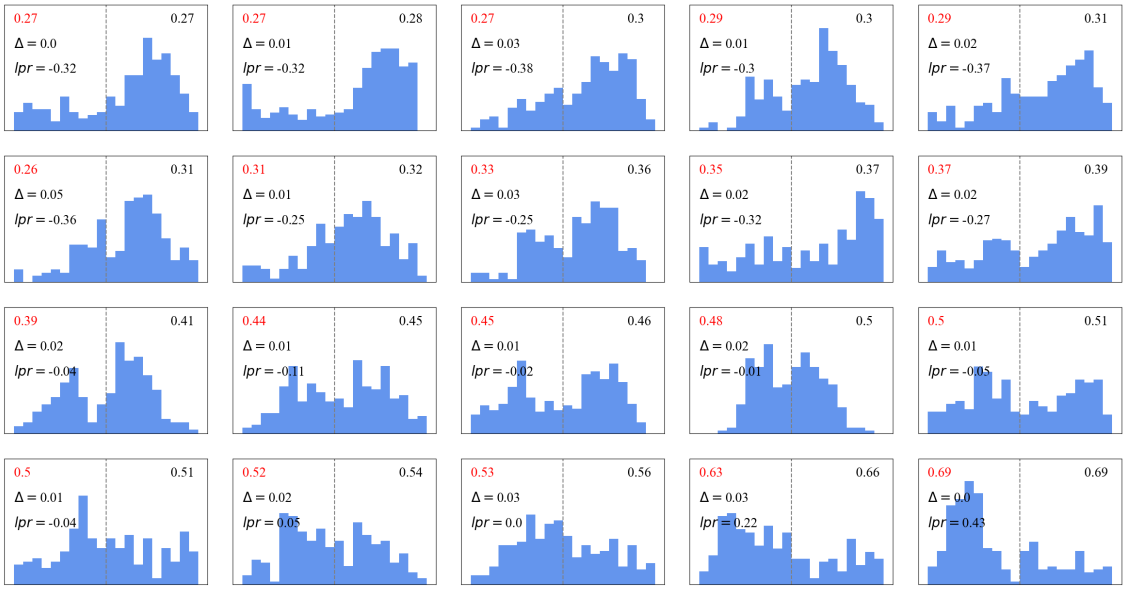
	sum sq	DF	F	PR(>F)
Diagnosis	0.012	1.0	1.12	0.29
Method	0.069	1.0	0.64	0.42
Diagnosis*Method	0.000	1.0	0.00	0.99
Residual	903	84.0		

Table 5.1 Results from the 2x2 ANOVA for with proportion of rapid responses as the dependent variable and diagnosis (between-subjects) and method (within-subjects) as the two independent variables.

As the difference between RR-Basic and RR-Model scores was non-significant, and there was no interaction with the method of scoring and diagnostic status, a group comparison using the RR-Model scores was not carried out. Instead, log probability ratio scores will



(a) Control participants



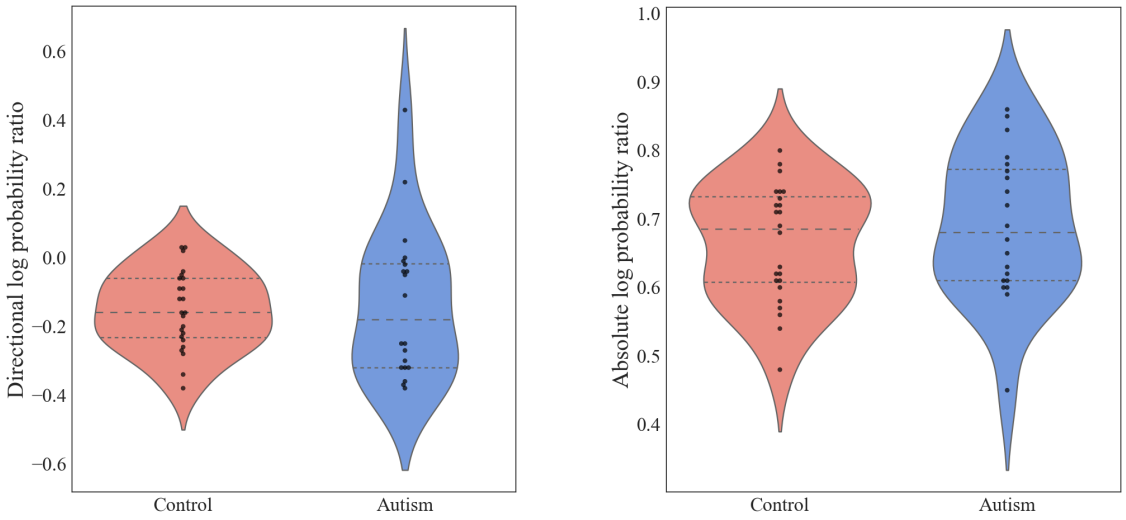
(b) Autistic participants

Fig. 5.5 Response distributions shown for all participants. The values in black in the top-right corner of each plot show the basic proportion of rapid responses calculated for each participant (RR-Basic) and the values in red in the top-left corner show the model based proportion of rapid responses (RR-Model). The difference between the values for the proportion of rapid responses estimated by the two different methods is also shown (Δ) as well as the accumulated directional log probability ratio (lpr). The original $t_{epoch} = 0.5$s threshold is shown on all plots as a dotted line.

be considered as these additionally accounted for the accumulated likelihood of the trial classifications.

5.3.3 Log probability ratio scores

Overall log probability ratio scores were calculated for each participant by sequentially updating the probabilities across the trials. Distributions of the log probability ratios across trials are displayed for all participants in figure B.1 in appendix B. Independence of trial outcomes was an assumption that needed to be met to use the approach detailed here, therefore a short analysis was conducted to verify that response types on concurrent trials were independent of one another. This was done individually at the participant level, to verify that this assumption held for all participants. For each participant, a correlation analysis was carried out across all trials to assess whether the occurrence of a rapid response on the previous trial ($trial_{n-1}$) was associated with the occurrence of a rapid response on the current trial ($trial_n$). This relationship was found to be non-significant for all participants and therefore supported the assumption that response types were independent across trials.



(a) Directional log probability ratios

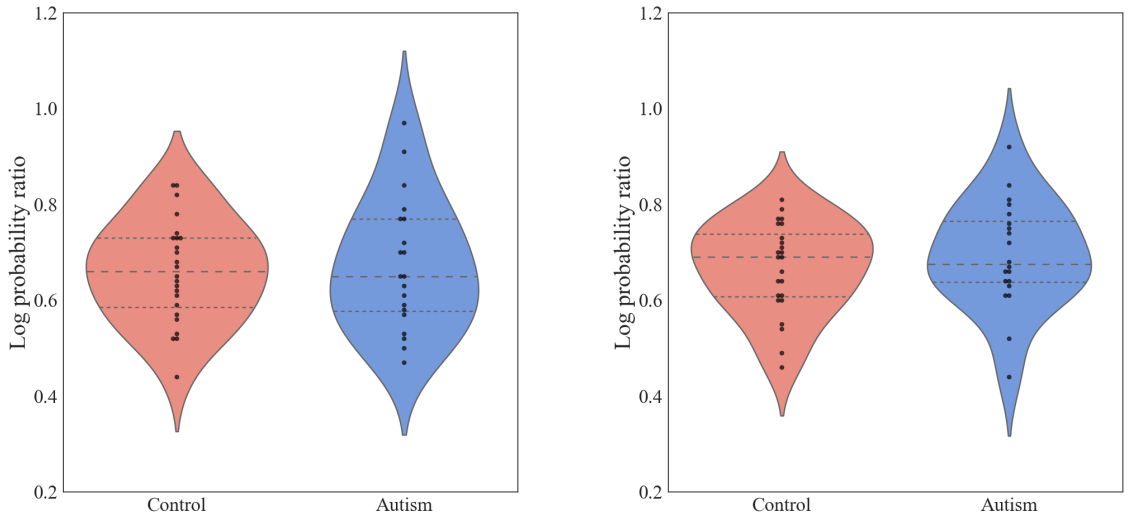
(b) Absolute log probability ratios

Fig. 5.6 Violin plots showing the cumulative directional (a) and absolute (b) log probability ratios for autistic and non-autistic pariticpants. individual data points show the log probability ratios for all participants in the two groups. Dashed horizontal lines are overlaid to show the median, upper quartile and lower quartile of each groups distribution.

A Levene's test on the directional log probability ratio scores revealed that they had unequal variances across the two groups (F = 8.55, p = 0.006) and so a Welch's t-test was used to compare the group means. Control participants average directional log probability ratio (M = -0.153, SD = 0.114) was similar to that of the autistic participants (M = -0.135, SD = 0.217) and the two groups did not significantly differ from each other $t(27.6) = 0.324$, $p > 0.3$. Absolute values of the log probability ratio were also considered to gauge the overall

confidence of the classifications for each participant. The Levene's test revealed that they had equal variances across the two groups ($F = 0.94$, $p > 0.3$). The control groups average absolute log probability ratio ($M = 0.665$, $SD = 0.085$) was again similar to that of the autism group ($M = 0.691$, $SD = 0.106$) and the two groups did not differ significantly from each other $t(42) = 0.91$, $p > 0.3$. Distributions of direction and absolute log probability ratios are displayed in figure 5.7.

For the response type specific log probability ratios, a 2-way ANOVA was carried out using log probability ratio as the dependent variable, diagnostic status (group) as the between-subject measure and response type as the within-subject measure. Neither of the main effects for diagnostic status ($F_{(1,84)} = 0.704$, $p > 0.3$) or response type ($F_{(1,84)} = 0.281$, $p > 0.3$) were found to be significant, nor was there a significant interaction effect between diagnostic status and response type ($F_{(1,84)} = 0.087$, $p > 0.3$). Full output from the analysis is shown in table 5.1 in appendix A and distributions of absolute log probability ratios for the two response types are displayed in figure 5.6.



(a) Rapid responses.

(b) Slow Responses.

Fig. 5.7 Violin plots showing the cumulative absolute log probability ratios for rapid responses (a) and slow responses (b). Individual data points show the log probability ratios for all participants in the two groups. Dashed horizontal lines are overlaid to show the median, upper quartile and lower quartile of each groups distribution.

Effects of motor reaction times on rapid resumption

Pearson correlation tests were again used to assess whether the extent to which participants used prior information to facilitate visual search was associated with basic motor reaction

times. This time, the analysis was conducted using median reaction times in the non-distractor control task and the directional log probability ratios from the main task. This was again carried out separately for the two groups to assess whether the relationship between these variables differed between the two populations. Similarly to the results in the previous chapter, the direction of association differed between the groups but neither the correlation in the control group (r = -0.237, p = 0.265) or in the autism group (r = 0.273, p = 0.245) reached significance. These two correlations are shown in figure 5.8.

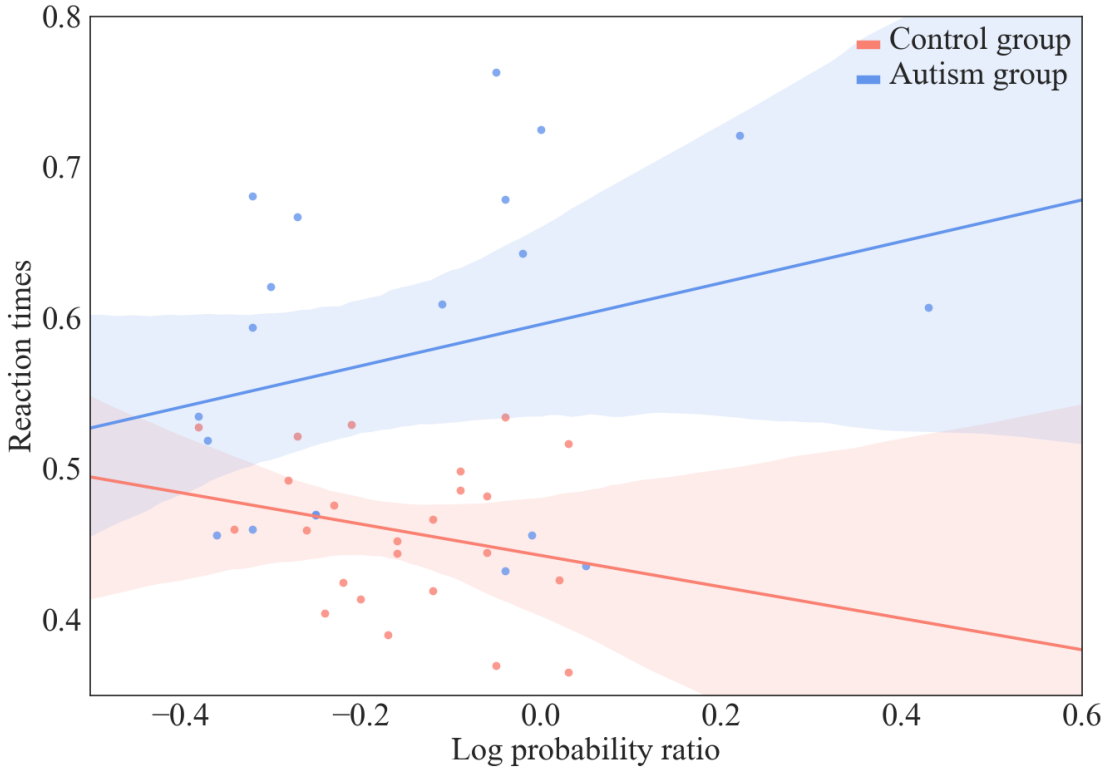
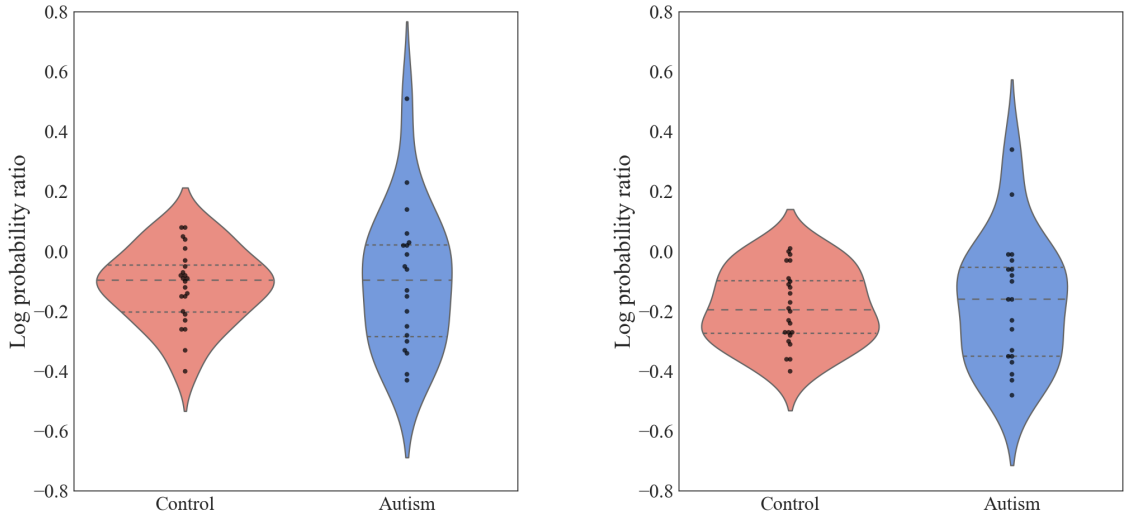


Fig. 5.8 Correlations between median reaction times in the control task and direction log probability ratios from the main task. Data are shown separately for autism and control groups.

Effects of distractor density on rapid resumption

The effect of distractor density on the extent to which prior information is used during visual search was again assessed, this timing by calculating directional log probability ratios separately for low- and high-distractor conditions for each participant. The distributions of scores for both groups across the two conditions are shown as violin plots in figure 5.9.



(a) Low distractor condition

(b) High distractor condition

Fig. 5.9 Violin plots showing the log probability ratios for low distractor density trials (a) and high distractor density trials (b). Individual data points show the log probability ratios for all participants in the two groups. Dashed horizontal lines are overlaid to show the median, upper quartile and lower quartile of each groups distribution.

A 2x2 ANOVA was conducted using log probability ratios as the dependent variable, condition (low distractor vs high distractor) as a within-subject factor and group (control vs autism) as a between-subjects factor. The results from the ANOVA were similar to the results from the previous chapter where RR-Basic scores were used as the dependent variable. There was no significant effect of group ($F_{(1,84)} = 0.254$, $p > 0.3$) or condition ($F_{(1,84)} = 3.523$, $p = 0.064$) on log probability ratios. The interaction between group x condition was also non-significant ($F_{(1,84)} = 0.000$, $p > 0.3$). Results from the ANOVA are summarised in table 5.2. Similar results were found using absolute log probability ratios and are shown in table A.2 in appendix A.

	sum_sq	df	F	PR(>F)
Group	0.007911	1.0	0.253558	0.615899
Condition	0.109910	1.0	3.522796	0.064002
Group*Condition	0.000002	1.0	0.000059	0.993864
Residual	2.620776	84.0		

Table 5.2 Results from the 2x2 ANOVA with log probability ratio scores as the dependent variable and distractor condition (within-subjects) and group (between-subjects) as the two independent variables.

5.4 Discussion

In this chapter, I was able to successfully fit a Gaussian mixture model to the pooled participant response data. This allowed me to obtain estimates for the parameters of the distinct distributions for rapid responses and slow responses. The Expectation-Maximisation algorithm converged on a 2-component model, suggesting that the response distributions for standard responses were indeed bimodal. The model parameters that I found were then used to calculate a more accurate classification threshold (the exact time at which a response is equally likely to be a rapid response or a slow response) by minimising the log probability ratio between the two Gaussian distributions. This classification threshold was found to be very close to the value used by Lleras et al. (2011a). The value calculated by the model was 448ms, which was only marginally different from the approximate value (500ms) suggested by Lleras et al. (2011a). This indicates that the previous method used for classifying trials was suitable for inferring response types from participant reaction times and therefore the results obtained using this approach are reliable. Furthermore, there were no significant differences between the ratio scores calculated using the two methods. This suggests that the approach used by Lleras et al. (2011a) produces similar results to the data driven approach detailed in the present chapter.

This provides further evidence to support the findings from previous chapter, which suggested that both the control and the autism groups were able to use prior information to facilitate visual search to a similar extent. The modelling approach developed in this chapter has the added advantage of allowing for the likelihood of each trial classification to be considered. This method provides a richer set of measures which could be sensitive to variation in task performance that would be overlooked by only considering the relative proportions of response types. However, in the case of the present dataset I was still unable to find any significant differences between the two groups using any of the log probability ratio measures. This further supports the evidence for there being intact use of prior information during the search task in the autism group. Overall, the results obtained in this chapter and the previous chapter provide evidence that individuals with autism are able to use prior information to facilitate visual search and guide attention to a similar extent as non-autistic individuals.

This study is not the first to report findings that conflict with the suggestions that autistic individuals may display an attenuated use prior information during perception. A number of other studies have previously attempted to directly investigate the claims of Pellicano and Burr (2012b) across a variety of different tasks. Several of these reported evidence that suggested there was intact use of prior information in autistic individuals. One such study looked at whether autistic individuals showed an expectation for direct gaze, an innate

prior which biases people to expect that other people's gaze tends to be directed at them (Mareschal et al., 2013). This effect was found in autistic individuals, suggesting that this expectation develops similarly in autism to non-autistic individuals (Pell et al., 2016). The 'light-from-above' prior is another commonly observed expectation effect. This term refers to a perceptual bias towards assuming shadows are created by a light source above the object of interest, a mechanism which is used when inferring the shape of an object from it's shading. While this effect has been suggested to be an innate expectation in humans (Geisler and Kersten, 2002; Scholl, 2005), the extent of this effect is influenced by experience (Adams et al., 2004). This effect has also been showed to be intact in autistic children (Croydon et al., 2017).

Other studies have focused on experimental paradigms in which expectation effects were developed during the task rather than acquired innately. For example, Karaminis et al. (2015) showed that adaptation to causal events was similar in autistic children when compared to typically developing controls. One method that has frequently been used to gauge the extent to which individuals are able to utilise prior information is ensemble perception. This refers to the extraction of summary statistics for a certain stimulus property within a set of items (Haberman and Whitney, 2012). It is suggested that ensemble perception represents a form of prior expectations of item representations across a set of items rather than in the form of individual item representation (Allik et al., 2014). Indeed, ensemble perception has been used as a method for assessing the claims of Pellicano and Burr (2012b) across a number of studies (der Hallen et al., 2017; Karaminis et al., 2017; Lowe et al., 2018; Maule et al., 2017). These studies have reported mixed findings, with some reporting intact ensemble perception in autism and others reporting reduced levels of ensemble perception. While these studies all focus on ensemble perception, they each look at different cognitive domains. It may be that a reduced influence of prior information only occurs under specific conditions or within certain domains.

Another interesting finding within this set of studies comes from Maule et al. (2017), who examined ensemble perception of colour hues in autistic individuals. While they did report a significant difference between autistic and non-autistic participants in averaging across ensemble sets of colours, with the autistic group performing the task less accurately than the control group, this result only held for the smallest set size of ensembles tested. When averaging was assessed across larger sets, the two groups performed similarly. This result highlights how task difficulty may potentially influence the extent to which potential group differences are observable. The results from the interrupted search task presented here did include one manipulation of difficulty, by including trials with both low- and high-distractor densities in the task (with either 16 or 32 items in the search display respectively). However,

the analyses suggested that there was no interaction effect between diagnostic status and distractor density. This provides some evidence to suggest that, in the case of the present study, the lack of difference between the autistic group and controls is not due solely to insensitivity of the task due to the difficulty level either being too low or too high. However, a wider range of conditions should be considered before drawing any firm conclusions.

While the thorough analyses presented here found little difference between the behavioural performance of the autistic and non-autistic participants, this does not rule out the potential explanation that distinct cognitive strategies could have been used but still resulted in non-distinguishable performances in the task between the two groups. This potential explanation of the results would need to be assessed directly using neuroimaging techniques. Indeed, the interrupted search paradigm has been used in a study looking at the neural mechanisms of prediction during visual search (Spaak et al., 2016). In this study, magnetoencephalography imaging was used alongside an interrupted search paradigm and the authors were able to find specific neural signals which related to participants' awareness of target location and target identity. They were also able to show that rapid responses were associated with the occurrence of these neural signals and their results suggested that the generation of these sensory predictions involved the medial superior frontal cortex and the right temporo-parietal junction. This approach could be expanded to assess whether autistic individuals show the same patterns of activity as non-autistic individuals. Additionally, imaging methods could allow for the distinct stages of attention in visual search to be considered separately (Eimer, 2014). Specifically, prior information is thought to facilitate visual search by influencing either the guidance or response selection aspects of attention (Kunar et al., 2007b, 2008). The specific mechanisms influenced by prior expectations are not easily inferred using only behavioural paradigms and so imaging approaches may help to shed light on the specific stages at which prior information affects performance (as illustrated in figure 5.10).

One limitation of both the approach used by Lleras et al. (2011a) and the method developed in this chapter, is that fixed parameters are used to classify the response types across all participants rather than adopting an individualised approach. It may be the case that the best estimates for the parameters of the underlying response distributions vary across individuals and therefore using an approach that estimates the model parameters based on data from the entire sample might lead to less accurate modelling of the response types. Fitting Gaussian mixture models to single participant data is one possibility for overcoming this issue, however this may introduce other difficulties in the modelling process due to a reduction in the number of observed data points available to fit the model. Increasing

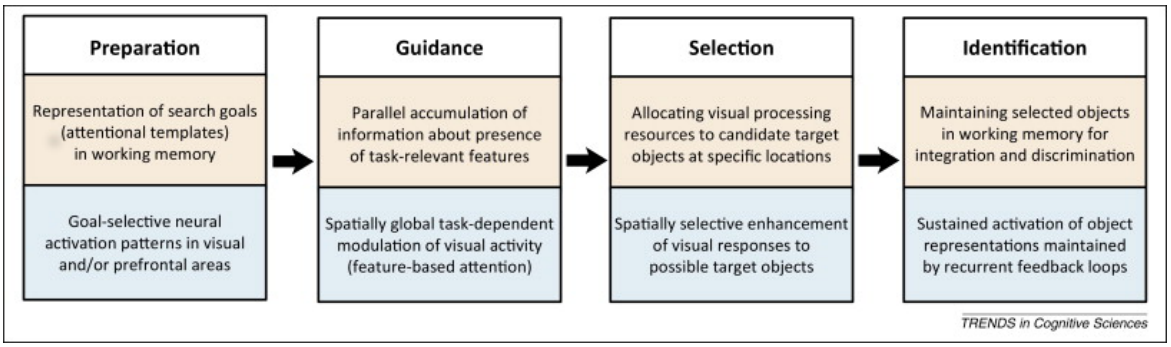


Fig. 5.10 The four-stage model of selective attention in visual search described by Eimer (2014). The four successive stages of attentional processing are represented as preparation, guidance, selection, and identification. The specific cognitive functions of each of these stages are shown in the orange boxes and neural processes for each stage are detailed in the blue boxes.

the number of observed trials could possibly overcome these difficulties while allowing for subjective modelling to be carried out across individual participants.

This is one of the first studies to look at whether autistic individuals are able to use prior information to guide attention. Contrary to the predictions made by Pellicano and Burr (2012b) and other related accounts, the results suggested strong evidence to suggest that autistic individuals show intact use of prior information during an interrupted visual search task. Visual search is a complicated mechanism and various other forms of search, such as conjunction search (McElree and Carrasco, 1999; O'riordan et al., 2001; Plaisted et al., 1998b), should be assessed before drawing wider conclusions. Nonetheless, this study provides a clear case of an instance in which the hypo-priors account does not hold. This implies that the account should possibly be reformulated to account for this and other cases in which evidence of intact use of prior expectations have been demonstrated in autistic samples.

Part III

Sequential learning

Chapter 6

Sequential learning of probabilistic outcomes in autism

Overview

In this chapter, a probabilistic version of the serial reaction time task was used to assess the implicit acquisition of predictive information. The design of the task allowed for continuous assessment of how prior expectations were built up over the duration of the task. A probabilistic reversal was included in the task to assess whether autistic individuals were able to update their expectations in a similar manner to the non-autistic controls.

6.1 Background

Sequential learning is vital for associating and grouping small actions in order to develop complex, high-order skills (Shima et al., 2007). The ability to represent sequences of movements at an abstract level is thought to be the basis for the development of a range of core skills such as rule learning, decision making and numerosity (Chafee and Ashe, 2007). The implicit acquisition of sequences of actions or events often occurs during the early stages when learning high-order associations and can lead to the ability to predict and expect future events (Keele et al., 2003; Robertson, 2007). Sequential learning is one of the more common ways of assessing implicit learning by using behavioural tasks with either a deterministic or probabilistic temporal structure. Impairments in sequential learning have been reported

across a number of different neurological conditions and learning difficulties such as specific language impairments (Lum et al., 2014), dyslexia (Lum et al., 2013) and Huntington's disease (Knopman and Nissen, 1991). Conversely, sequential learning has been shown to be heightened in some conditions such as Tourette syndrome (Takács et al., 2018).

Since its introduction, the serial reaction time task has been a popular method for assessing implicit learning (Nissen and Bullemer, 1987). The task requires participants to use a number of buttons or keys, commonly 4, to respond to corresponding targets on a visual display. Unbeknown to the participants, the positions of the targets, and therefore the corresponding keypresses, are not randomly assigned and are instead defined by a sequence. Reaction times can be analysed to assess the extent to which participants are implicitly aware of these underlying sequences. The task has been developed to have different levels of complexity and is now widely used (Robertson, 2007). The serial reaction time task has previously been used to assess sequential learning in autistic individuals. One of the earliest studies using this task in autistic children found that children with a diagnosis tended to perform worse than non-autistic controls (Mostofsky et al., 2000). Rinehart et al. (2001) carried out a similar study and reported a deficit in autistic individuals specifically in motor preparation rather than motor execution. Another study reporting deficits in autistic individuals on the serial reaction time task assessed how performance changed over longer durations of learning (Gordon and Stark, 2007). They found that implicit learning did occur in autistic individuals, but only after increased exposure to the sequence. While these studies all found differences between autistic and non-autistic participants, it is worth noting that the tasks used in these studies consisted of fixed, deterministic sequences that were relatively easy to learn.

More recent studies have introduced more sophisticated versions of the serial reaction time task which allow for reaction time differences between expected and unexpected trials to be compared. Barnes et al. (2008) did this by using an alternating serial reaction time task in which the required key presses alternated between being determined by a sequence and being randomly positioned. Their results also showed a lack of differences between the autistic and non-autistic participants. Nemeth et al. (2010) used a similar alternating version of the serial reaction time task and, again, found intact implicit learning in autistic individuals. Travers et al. (2010) also assessed performance on the serial reaction time task in autistic individuals but specifically aimed to address some potentially problematic issues with the sequences used in previous studies. They ensured their sequence was well-balanced and only contained second-order conditional information using a sequential structure suggested previously by Jimenez and Vazquez (2005). In this sequence, each of the different target positions were equally likely to be followed by each of the other three target positions, which was not the case in the previous studies discussed (Gordon and Stark, 2007; Mostofsky et al., 2000;

Rinehart et al., 2001). However, the sequential blocks in their task were still deterministic by design. Their results were inline with those of Barnes et al. (2008) and Nemeth et al. (2010), again finding intact implicit performance in individuals with autism.

In the first of a series of studies looking at implicit learning in autism, Zwart et al. (2017) assessed implicit learning ability in adults with and without autism at both the behavioural and neural level. At the behavioural level, they combined both deterministic and probabilistic structures in their serial reaction time task and their results suggested the autistic and non-autistic adults performed similarly. However, they found distinct difference between the two groups when they considered event-related potentials (ERPs) during the task. Their results found that N2b and P3 signals were enhanced in the control and autism group respectively, suggesting that the control group showed a higher degree of incidental learning whereas the autism group showed more effortful learning. The same research group also considered differences in implicit learning between children with autism and non-autistic controls (Zwart et al., 2018a). Again, differences were only observed when considering the ERPs during the task as behavioural performance was similar between the two groups. Autistic children showed a tendency to rely mainly on incidental learning and were less reliant on explicit processes relative to the non-autistic children who used both explicit and implicit processes during the tasks. Their findings in autistic children were contrary to those reported in autistic adults and, when taken together, suggest that autistic adults may differ from autistic children based on the fact that they tend to rely more on explicit forms of learning and rely to a lesser extent on implicit processes. The same authors also took behavioural data from their adult study (Zwart et al., 2017) and combined it with an additional sample to look at whether a correlation existed between performance on the serial reaction time task and social impairments (Zwart et al., 2018b). They reported an association when using performance obtained during a deterministic version of the task but didn't find any association when considering performance in a probabilistic version of the task. While meta-analyses of the literature have reported evidence in support of an absence of differences between implicit learning in autistic and non-autistic individuals (Foti et al., 2015; Obeid et al., 2016), the studies considered in these analyses have been relatively limited in the level of complexity at which information was presented to participants.

One version of the serial reaction time task which has an entirely non-deterministic structure was used by Kaufman et al. (2010) to explore the relationship between implicit learning and a number of different cognitive and personality measures. Their version of the task used two distinct second-order conditional sequences both of which were in line with the design of Jimenez and Vazquez (2005). The target position in the task was determined in a probabilistic manner, by using a random variable of a specific probability to select

which of the two sequences would be used to determine the next position. The probablistic selection of which sequence to use was done in such a way that one of the two sequences would be presented more frequently to participants and would therefore be expected more than the alternative sequence. Kaufman et al. (2010) discuss the strengths of this version of the serial reaction time task as a method for assessing implicit learning. They suggest that the serial reaction time task in general is a much better measure of incidental learning than alternatives, such as artificial grammar learning tasks, as it avoids giving participants explicit instructions to extract rules from the task. In particular, probabilistic forms of the serial reaction time are thought to have a lower chance of explicit awareness occurring than versions using deterministic sequences and performance is affected to a lesser extent in the case that explicit learning does occur (Stefaniak et al., 2008). The fact that there are no deterministic transitions within the sequence suggests that it better captures aspects of real-world learning, which tend to occur under conditions of uncertainty (Jimenez and Vazquez, 2005). The authors also used post-experiment interviews to show that participants lacked any explicit awareness of the underlying task structure (Kaufman et al., 2010).

Incidences of statistical learning in real-world settings are likely to occur under conditions of uncertainty (Jimenez and Vazquez, 2005). Thus, it is more ecologically valid to test implicit learning abilities using tasks where the information is probabilistic, and has a higher degree of noise or uncertainty, than under highly predictable, deterministic conditions. As the majority of studies assessing implicit and statistical learning in autism have used deterministic structures (Foti et al., 2015; Obeid et al., 2016), it is not clear whether the findings from these studies will extent to non-deterministic environments. Furthermore, probabilistic versions of the serial reaction time task also allow for 'online' measurement of learning effects, as expected and unexpected trials are interspersed within the training phase of the task. This allows for learning rates to be assessed across the entirety of the behavioural task rather than just testing at an arbitrarily defined endpoint, which is particularly useful when testing for potential group differences.

Another question which has not been assessed in the statistical learning literature is whether autistic individuals perform similarly to non-autistic controls when the underlying statistical probabilities are dynamic rather than static, requiring participants to change or update their previous expectations. A number of studies have reported difficulties in reversal learning in autism, primarily in the context of reinforcement learning. These studies generally found that autistic individuals didn't differ significantly to the non-autistic controls when initially learning probabilities but displayed difficulties in updating and maintaining their expectations when the probabilities were reversed (D'Cruz et al., 2013; Solomon et al., 2011; South et al., 2012). It is not clear whether this result extends to situations in which participants

are not given direct feedback or explicitly informed about associations within task, as is the case in implicit or statistical learning paradigms. However, assessing whether autistic individuals display difficulties when required to implicitly update expectations may help to test claims that suggest autistic individuals update priors in an inflexible manner relative to non-autistic controls (Van de Cruys et al., 2014). Therefore, the aim of this chapter will be to assess whether autistic individuals show intact acquisition of predictive information in a probabilistic serial reaction time task and whether they are able to update their expectations, following a probabilistic reversal, in a similar manner to non-autistic controls.

6.2 Methods

6.2.1 Participants

A total of 64 participants completed the probabilistic serial reaction time task. All participants were right handed and had normal or corrected-to-normal vision. 30 of these participants had a diagnosis of an autism spectrum condition. Participants with a diagnosis of an autism spectrum condition were recruited from the Cambridge Autism Research Database (CARD) and control participants were recruited from the Cambridge Psychology Volunteers Database or through classified adverts on websites such as Gumtree. There were no significant differences between the two groups on age (Control group, $M = 29.46$, $SD = 8.65$; Autism group, $M = 32.82$, $SD = 9.51$; $t(67) = 1.517$, $p = 0.13$) or IQ (Control group, $M = 117.42$, $SD = 10.65$; Autism group, $M = 114.38$, $SD = 13.78$; $t(67) = 1.013$, $p > 0.3$).

6.2.2 Stimuli presentation

Stimuli were presented using the Psychtoolbox extension (Brainard, 1997; Kleiner et al., 2007) in MATLAB (MathWorks, 1989). Stimuli were displayed on a 24" monitor running at a resolution of 1920x1080. Participants were sat with a viewing distance of 60cm from the screen in a darkened room.

The task display consisted of 4 individual white squares on a grey background. Each of the white squares subtended a 3° x 3° visual angle. The squares were separated by a 1° gap and were positioned to be centred on the middle of the screen. On each trial, a cross was displayed within one of the white squares. The cross consisted of two diagonal line segments. Each of these line segments subtended a 4° visual angle. The two line segments were oriented at a 90° angle from each other and a 45° angle from the vertical axis (see figure 6.1).

6.2.3 Procedure

During each trial, a cross appeared in one of the 4 boxes and participants were required to respond to the location of the cross by pressing the 'z', 'x', 'n' or 'm' keys. These keys corresponded to the 4 different potential positions for the cross, from left to right respectively. The procedure is demonstrated in figure 6.1. Participants were instructed to respond as quickly as possible and were given audio feedback (a beep) for incorrect or slow responses (over 3000ms). Once the participant responded there was a 200ms period in which the cross was removed from its current box before the next trial was started. Participants completed 2 full sessions of the task and were given a 5-minute break in between sessions. Each session consisted of 8 blocks which each contained 120 trials. Participants were given a 30 second break in between blocks. The duration of the entire task lasted approximately 30 minutes.

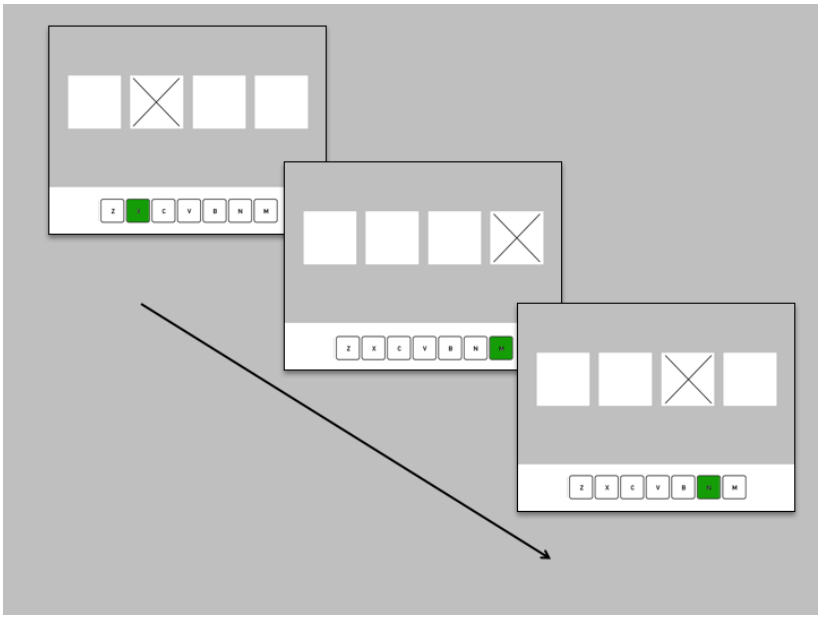
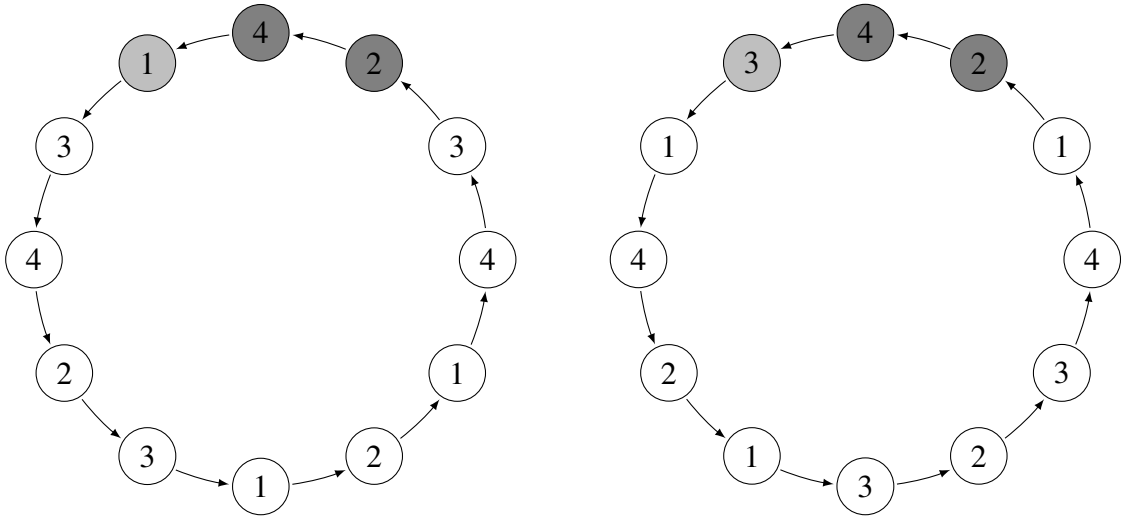


Fig. 6.1 Diagram showing an example of different positions of the target cross and the respective responses for each position.

6.2.4 Sequence generation

On each trial, the position of the target cross was determined based on its two previous positions by probabilistically selecting one of two distinct deterministic Markov-chain sequences. The two separate sequences that were used to determine the next position of the cross were selected 85% and 15% of the time respectively. The relative frequencies of each of the different target positions and the first-order transitions between positions were balanced

across the two sequences. The two sequences only differed in the second-order conditional information (Reed and Johnson, 1994). Figure 6.2 shows the order of both the probable transitions (sequence A) and the improbable transitions (sequence B). For each sequence, there is only one unique position based on the second-order conditional information. Thus, if the two previous positions of the target had been 2 and 4, there would be an 85% chance that the next position would be 1 (i.e. the probable transition determined by sequence A) and a 15% chance that the next position would be 3 (i.e. the improbable transition determined by sequence B). By implicitly learning this second-order conditional information, participants would be expected to develop expectations for the upcoming positions of the target based on the prior observed positions of the target. These expectations can be assessed by looking at reaction times across the task, with faster response times occurring during probable trials (where the target appears in a position dictated by sequence A) than during improbable trials (where the target appears in a position dictated by sequence B). Participants were initially given a 30-trial practice block in which target positions were determined with equal probability from the two sequences. After this, participants completed 2 sessions which each consisted of eight blocks of 120 trials each. During the first session, the probable and improbable sequences were as they are shown in figure 6.2. However, these two sequences were switched in the second session. This meant that sequence B determined the probable transitions and sequence A determined the improbable transitions during the second session.



(a) Sequence A (b) Sequence B

Fig. 6.2 Sequences consisting of probable transitions (a) and improbable transitions (b). The number shown in each node represents the target position (with 1 being the most leftward position and 4 being the most rightward). During the first session, there was a 85% chance of the target location being determined by sequence A (probable transitions) and a 15% chance of the location being determined by sequence B (improbable transitions). For any two-back context (possible combinations of the target location during $trial_{n-1}$ and $trial_{n-2}$) there were two possible following outcomes for $trial_n$. This is demonstrated in the figure, with the context [2,4] highlighted for both sequences in dark gray. The outcome positions for this particular context are shown for each sequence in light gray. For this context, there would be a 85% chance that the target would be in position 1 in the subsequent trial ($trial_n$) and a 15% chance it would be in position 3. In the second session the two sequences were switched, meaning there was a 85% chance of the target location being determined by sequence B (now the probable transitions) and a 15% chance of the location being determined by sequence A (now the improbable transitions).

6.2.5 Data analysis

Expectation effects were calculated by comparing differences in performance between trials in which the target position was generated using the primary sequence (probable trials) and trials in which the target position was generated using the secondary sequence (improbable trials). The expectation effect for a given period was calculated by subtracting the performance during probable trials from performance during improbable trials and then normalising the difference by dividing by the performance during probable trials. The formula used to calculate expectation effect can be summarised as follows:

$$E = \frac{P_{Improb} - P_{Prob}}{P_{Prob}} \tag{6.1}$$

Where P_{Prob} and P_{Improb} represent the performance measure for probable and improbable trials respectively and E is the expectation effect. The performance measure used could be reaction times, error rates (or proportion of correct responses) or inverse efficiency scores. Expectation effect was calculated using a sliding window for visualisation purposes and using binned trials for the main analysis. These calculations were done using a fixed number of trials for the probable and improbable trials respectively. This was to avoid potential bias from differences in the ratio of probable to improbable trials which could occur across the different time bins. The first 2 blocks of each session were considered training blocks and were not included in the main analysis. The remaining trials were put into time bins of 240 trials, the length of 2 blocks. This gave 3 time points (referred to as the start, middle and end) across each of the 2 sessions.

Reaction times were calculated using the median value for each participant over trials within the specific window. Proportion of correct responses were calculated by dividing the number of correct responses within the specified window by the total number of trials in that window. Inverse efficiency scores were calculated by dividing the median reaction time by the proportion of correct responses (or 1 - error rate) across the specified window. This gives inverse efficiency scores the same units as reaction times (seconds), with lower values on inverse efficiency scores indicating better performance.

6.3 Results

6.3.1 Preliminary analysis

The initial sample contained 30 autistic participants (16 male) and 34 control participants (20 male). A Chi-squared test was of the frequencies of males and females across the two groups

was non-significant, suggesting the ratio of male and female participants was balanced across the autism and control groups ($\tilde{\chi}^2(1) = 0.036, p > 0.3$). Error rates and reaction times were then considered to determine whether any participants performed significantly worse than the rest of the group on either of these measures.

Error rates

Initially, overall error rates across all trials were considered. These are shown for both groups in figure 6.3. A Levene's test for equal variances revealed that the two groups had unequal variances ($F = 4.58$, $p = 0.036$), therefore a Welch's t-test was conducted to test whether the two groups had equal expected means. Control participants ($M = 0.950$, $SD = 0.035$) were found to make significantly more incorrect responses than the autistic participants ($M = 0.967$, $SD = 0.023$) at the group level ($t(57.05) = 2.24$, $p = 0.029$).

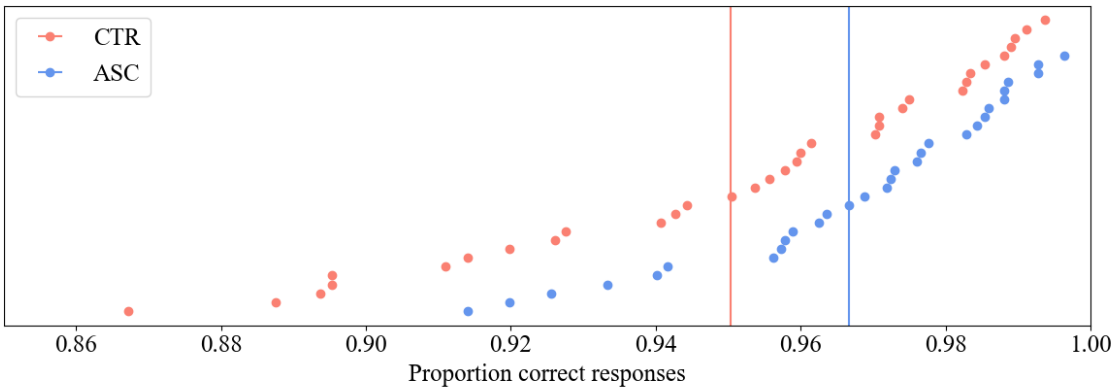


Fig. 6.3 Accuracy scores (the proportion of correct responses) across all trials in the task shown for participants in the control and autism groups, sorted in descending order. The filled vertical lines show the group means for the control (red, CTR) and autism (blue, ASC) groups.

Overall error rates were not a suitable criterion for identifying untypically poor performance due to the fact that an increase in error rates during improbable trials would be predicted in participants who showed a stronger influence of expectation effects in the task. Therefore, error rates were considered only for responses to probable trials during the first session. A Levene's test revealed that the two groups also had unequal variances on these subset error rates ($F = 4.82$, $p = 0.032$). Again, there was a significant difference between the two groups ($t(58.00) = 2.29$, $p = 0.025$) with control participants ($M = 0.956$, $SD = 0.031$) making significantly more incorrect responses than the autistic participants ($M = 0.971$, $SD = 0.021$). The subset errors rates are presented in figure 6.4, with the outlier cutoffs shown

(based on 2 standard deviations from the group mean). There were 2 participants in the control group and 2 participants in the autism group whose performance fell below 2 standard deviations of the group mean. These participants were removed from the sample for the main analysis. The t-tests for overall error rates and probable-trial error rates were repeated after the removal of these participants and remained significant.

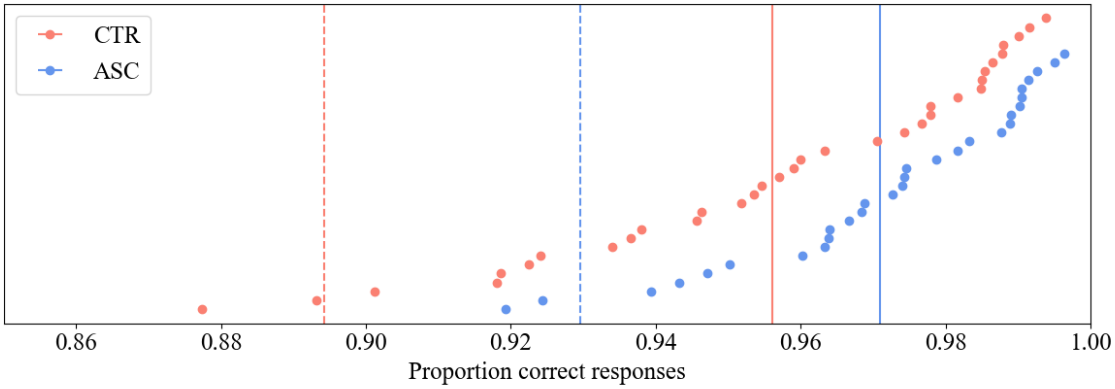
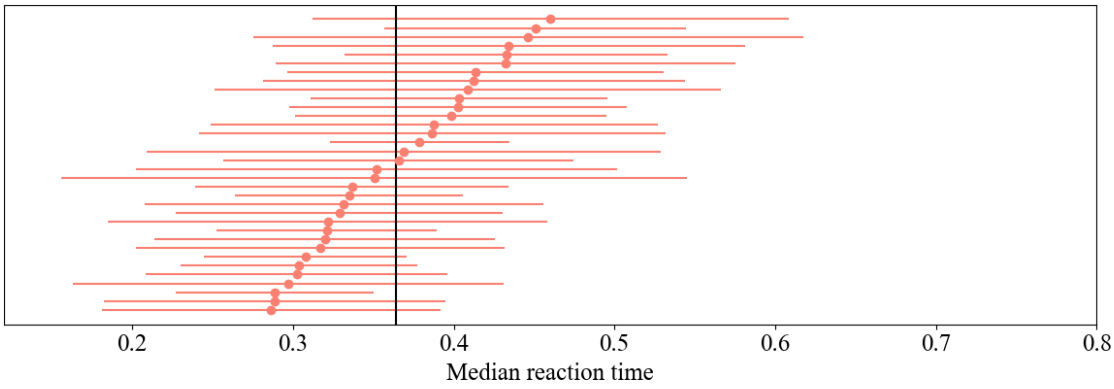


Fig. 6.4 Accuracy scores (the proportion of correct responses) across probable trials within the first session shown for participants in the control and autism groups, sorted in descending order. The filled vertical lines show the group means and the dashed vertical lines show the cut-off threshold for outliers for both the control (red) and autism (blue) groups.

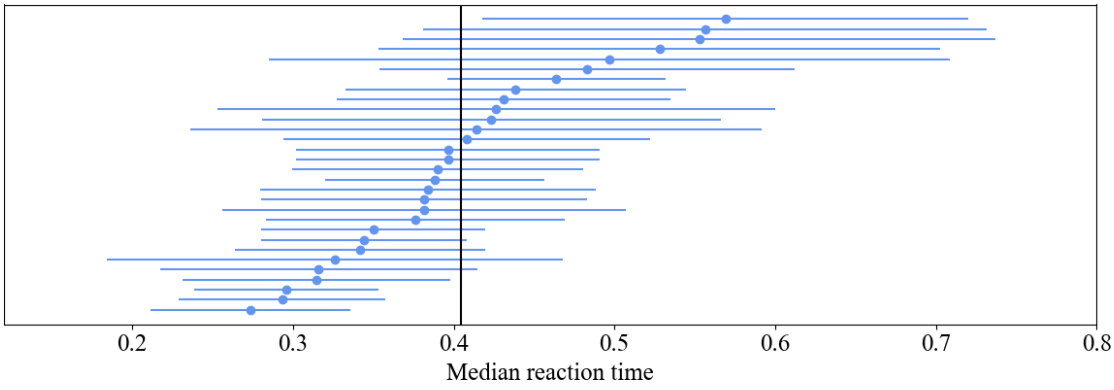
Reaction times

Similar to the approach taken for the error rates, median reaction times were initially considered across all trials. These are shown for the control and autism groups in figure 6.5. For median reaction times across all trials the two groups were found to have equal variances ($F = 1.96$, $p = 0.166$) and a t-test ($t(61.01) = 2.42$, $p = 0.018$) found that the control participants ($M = 0.364$, $SD = 0.054$) were significantly faster than the autistic participants ($M = 0.405$, $SD = 0.080$).

A greater influence of expectation effect would be expected to lead to increased reaction times during improbable trials, therefore overall reaction times were not deemed to be a suitable measure to gauge typical response speeds in participants. Instead, outliers were identified using median reaction times from probable trials with the first session of the task only. The two groups also had equal variances on reaction times across probable trials ($F = 1.20$, $p = 0.277$). However, a t-test found that while the control participants ($M = 0.377$, $SD = 0.061$) were again faster than the autistic participants ($M = 0.413$, $SD = 0.089$), this difference failed to reach significant ($t(57.05) = 1.90$, $p = 0.061$). These subset reaction times



(a) Control participants

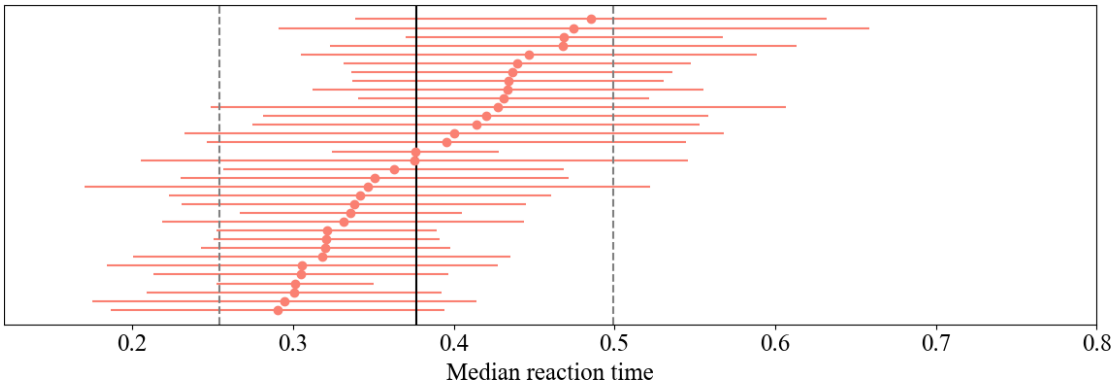


(b) Autistic participants

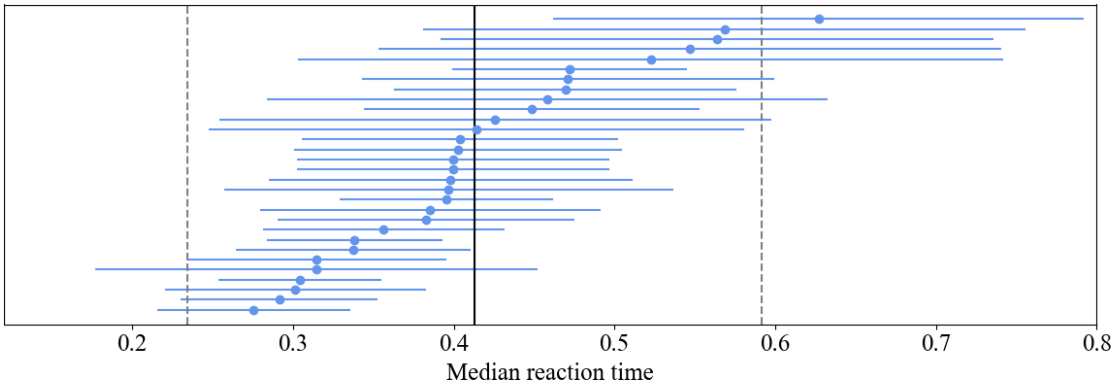
Fig. 6.5 Median reaction times for all trials across the entire task shown for participants in the control (a) and autism (b) groups, sorted in descending order. Horizontal bars shown standard deviations for each participant and vertical solid line shows the group means.

are presented in figure 6.6, with the outlier cutoffs shown (based on 2 standard deviations from the group mean). A single participant in the autism group was identified as an outlier and was removed from the sample for the main analysis. The t-tests for overall reaction times and probable-trial reactions were repeated after the removal of this participants and the results remained the same.

After removing outlier participants based on error rates and reaction times, the final sample contained 27 autistic participants (15 male) and 32 control participants (18 male). A further Chi-squared test was carried out to ensure the difference in frequencies of males and females across the two groups remained non-significant. The test was non-significant, suggesting the ratio of male and female participants was still balanced across the autism and control groups in the final sample ($\tilde{\chi}^2(1) = 0.439, p > 0.3$).



(a) Control participants



(b) Autistic participants

Fig. 6.6 Median reaction times for probable trials within the first session shown for participants in the control (a) and autism (b) groups, sorted in descending order. Horizontal bars shown standard deviations for each participant. Vertical solid lines show the group means and the dashed lines show the 2 standard deviation cut offs for both groups.

Speed-accuracy tradeoff

The results found in the previous analyses suggest that while the autistic participants performed better in terms of accuracy, the control participants gave faster responses. This combination of results suggests that the two groups might show different profiles in their tradeoff between speed and accuracy. This speed-accuracy tradeoff was further assessed for the two groups by carrying out analyses to test the strength of correlation between reaction times and error rates in these groups separately. This was initially done using reaction times and error rates from all trials across the entire task and then followed up by looking at reaction times and error rates from probable trials in the first session only.

When considering all trials in the task, there was a significant positive correlation between reaction times and proportion of correct responses in the control group ($r = 0.564$, $p > 0.001$). As performance is assessed in different directions across these two measures (with better performance being associated with higher values in terms of proportion of correct responses but lower values in terms of reaction times) this indicates towards a tradeoff between these two measures in the control participants. This relationship failed to reach significance in the autism group ($r = 0.349$, $p = 0.074$). However, the correlations did not differ significantly between the two groups ($Z = 0.99$, $p > 0.3$ *two-tailed test*) and the two measures were significantly correlated when the analysis was repeated without stratifying participants based on their groups ($r = 0.483$, $p > 0.001$). These correlations are shown in figure 6.7. The same analyses were carried out using only probable trials within the first session. Again, there was a significant positive correlation between reaction times and proportion of correct responses in the control group ($r = 0.528$, $p = 0.002$) but not in the autism group ($r = 0.369$, $p = 0.058$). This difference again failed to reach significance ($Z = 0.73$, $p > 0.3$ *two-tailed test*) and there was a significant correlation when data from both groups were combined ($r = 0.470$, $p > 0.001$).

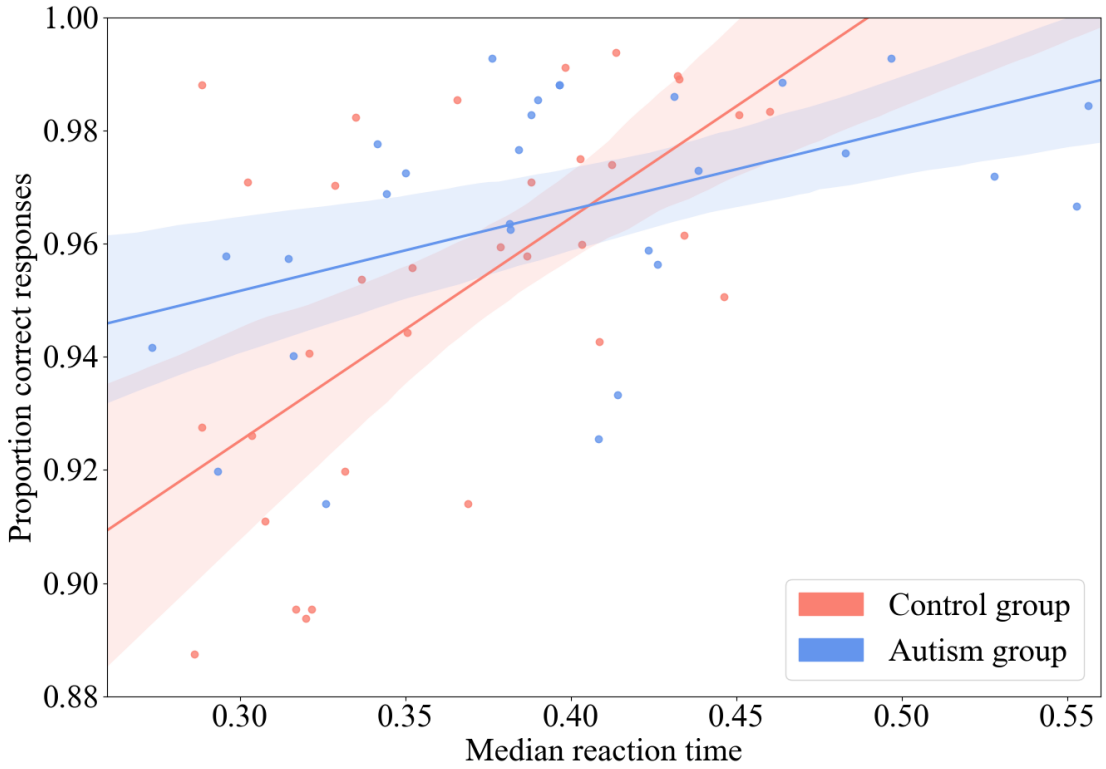


Fig. 6.7 Correlations between median reaction times and the proportion of correct responses for all participants. Control participants (red) and autistic participants (blue) are shown separately. Solid lines indicate the lines of best fit and shaded regions show the standard errors.

Inverse efficiency scores

The result from the previous section suggest that there is an interaction between error rates and reaction times which, although the group differences did not reach significance, may vary between autistic and control participants. Potential issues due to between-participant variation in speed-accuracy tradeoff can be accounted for by calculating inverse efficiency scores as detailed in the methods section. Average inverse efficiency scores were initially calculated across the entire task to allow for group comparison. A Levene's test revealed that the two groups had equal variances on inverse efficiency scores ($F = 1.92$, $p = 0.171$). There was a significant difference between the two groups ($t(55.34) = 2.11$, $p = 0.039$) with control participants ($M = 0.384$, $SD = 0.073$) scoring significantly lower than the autistic participants ($M = 0.418$, $SD = 0.050$). Overall inverse efficiency scores for individual participants are shown in alongside the group distributions in figure 6.8.

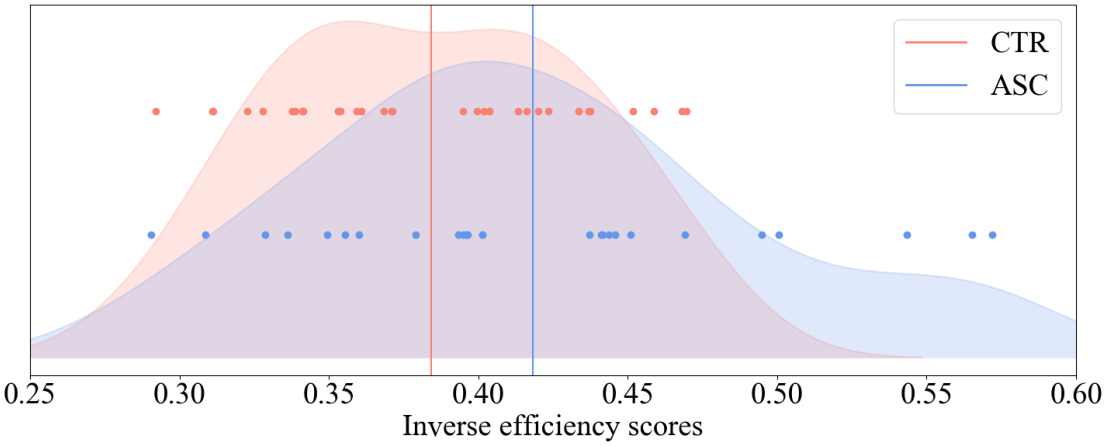


Fig. 6.8 Inverse efficiency scores across all trials in the task shown for participants in the control and autism groups. Individual data points are shown for all participants and kernel density estimates of the distributions of scores are shown for both groups. The filled vertical lines show the group means for the control (red) and autism (blue) groups.

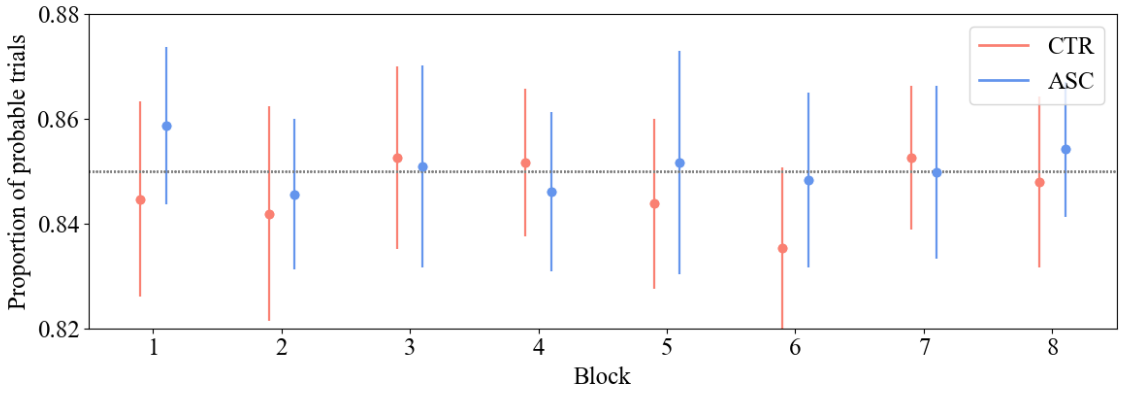
6.3.2 Expectation effect

In order to assess the extent to which participants were influenced by the underlying statistical probabilities of the trial sequence, and how this changed across the duration of the task, a sliding window approach was then used to calculate inverse efficiency scores on a trial by trial basis. IES scores were calculated separately for probable and improbable trials and then used to calculate the expectation effect as detailed in the methods section. Before carrying out analyses to assess changes in expectation effect over time, an additional analysis was carried out to determine whether there was evidence to suggest that the trial sequences presented to the two groups differed in the proportion of probable and improbable trials that occurred across any of the blocks.

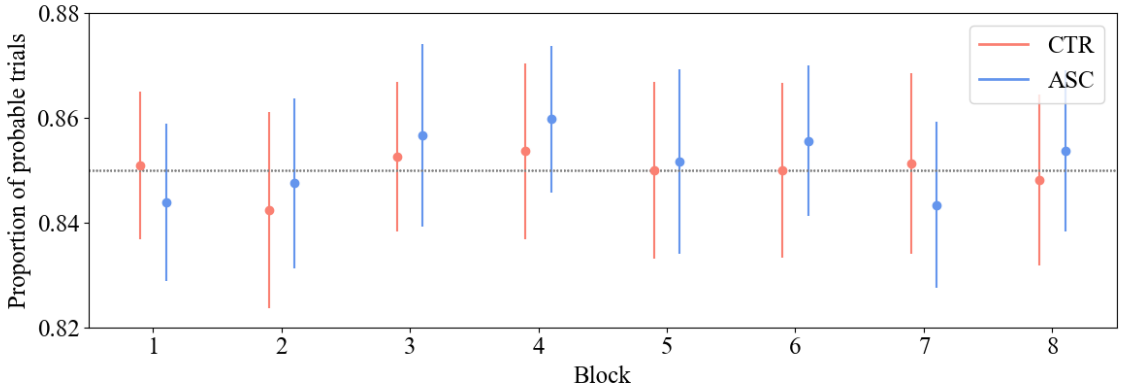
Proportion of probable trials

There two groups had equal variances for proportion of trial types for session 1, session 2 and the overall task. T-tests were found to be non-significant for session 1 trials ($t(62.54) = 1.53$, $p = 0.132$), session 2 trials ($t(62.54) = 0.58$, $p > 0.3$) and all trials across the task ($t(62.54) = 1.41$, $p = 0.164$). To test whether the groups differed across any of the individual blocks, additional t-tests were carried out for each of the 16 blocks across the two sessions. Despite taking a liberal approach by not applying any corrections for multiple testing, none of these

tests reached nominal significance (all p-values > 0.3). The ratio of probable to improbable trials across all 16 blocks are shown for both groups in figure 6.9.



(a) Control participants



(b) Autistic participants

Fig. 6.9 The proportion of probable trials across the all blocks in the first session (a) and second session (b) of the task. Mean values are plotted separately for control (red) and autistic (blue) participants and standard deviations for the group are shown by the vertical bars. The dotted horizontal line shows the expected proportion of probable trials (0.85) based on the generative model used to create the sequences.

Bayesian t-tests were also used to evaluate the evidence in favour of the null hypothesis (Marsman and Wagenmakers, 2017) in order to determine further whether there appeared to be a lack of differences between the ratio of probable and improbable trials between the two groups. When testing for differences across the individual blocks, the evidence in favour of the null (BF_{01}) ranged between 1.221 - 3.947. This equates to a modest to moderate amount of evidence to support the null (Dienes, 2014; Goodman, 2005). The equivalent values in support of the alternative hypothesis (BF_{10}) did not rise higher than 0.819 and were as low

as 0.253, suggesting there is little evidence to support alternate hypothesis that the groups differed in the proportion of trial types in any of the blocks. The results for all trials in the first session (BF_{01} = 1.495, BF_{10} = 0.669), second session (BF_{01} = 3.480, BF_{10} = 0.287) and entire task (BF_{01} = 1.735, BF_{10} = 0.576) were all similar outcomes. Overall, the results suggest that the two groups did not differ in the proportion of probable and improbable trials that occurred across individual blocks, sessions or the overall task.

Relationship between reaction times and expectation effect

Before assessing changes in expectation effect across the entire task, I assessed whether reaction times were correlated with measure for expectation effect. This was to determine whether there was any evidence to suggested that the speed at which a participant reacted to stimuli was associated with variation in expectation effect, either by affecting the sensitivity of the measure or affecting the rate at which the participant acquired an understanding of the underlying statistics of the task sequence. This relationship failed to reach significance for either the control participants (r = -0.311, p = 0.083) or the autistic participants (r = -0.081, $p > 0.3$). Data for participants in both groups are shown in figure 6.10. Due to a lack of evidence to support a relationship between reaction times and expectation effect, participant reaction times were not included as a covariate in the final analysis.

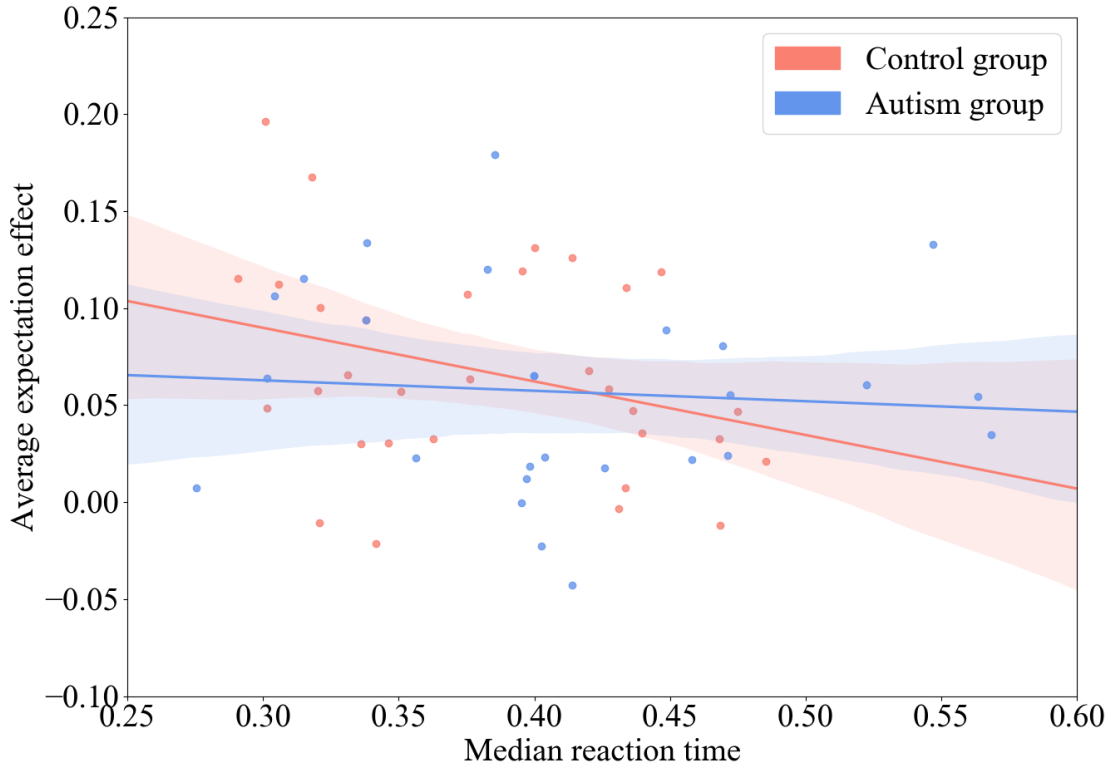


Fig. 6.10 Correlations between median reaction times and the average expectation effect for all participants. Control participants (red) and autistic participants (blue) are shown separately. Solid lines indicate the lines of best fit and shaded regions show the standard errors.

Expectation effect over time

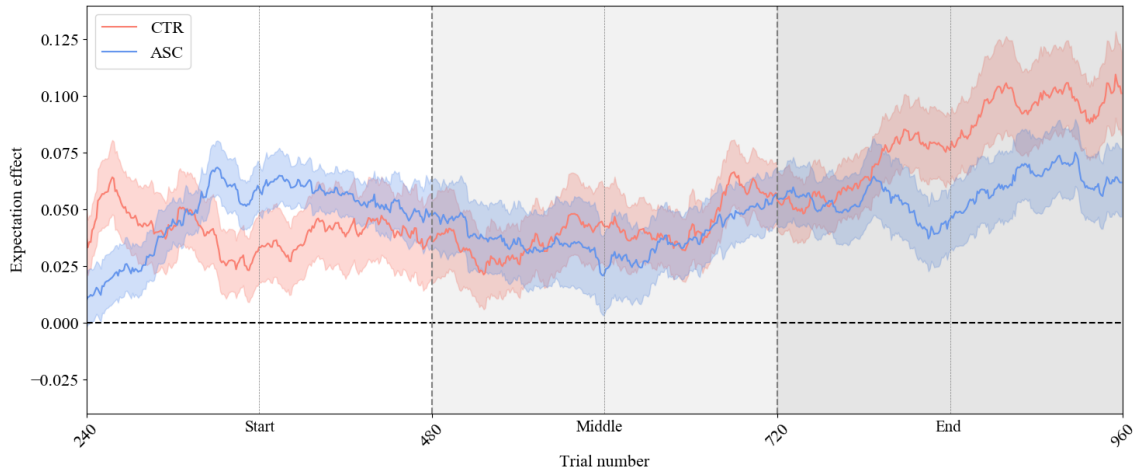
A sliding window approach was used to calculate expectation effect across all trials for visual purposes. These values are shown in figure 6.11. To assess the effects of learning across each session, average expectation effects were calculated over 240 trial windows (the length of two blocks). To be more precise and avoid potential biasing effects from variable proportions of probable and improbable trials, these 240 trial windows included exactly 85% probable trials (204) and 15% improbable trials (36). Based on piloting, learning effects were not established until after 2 blocks. Therefore, the main analysis only included data from blocks 3-8 in each session. Average expectation effect was calculated across three 240 trials windows within each session, between trial 240 and 480 (1200 and 1440 in the second session), between trial 480 and 720 (1440 and 1680 in the second session) and between trial 720 and 960 (1680 and 1920 in the second session). These three windows are referred to as the start, middle and end positions within the session. A three-way repeated measures

ANOVA was carried out, with expectation effect as the dependent variable. Position within the session (start v middle v end) and session (first v second) were included as within-subject factors. Diagnostic status (control v autism) was included as a between-subjects effect.

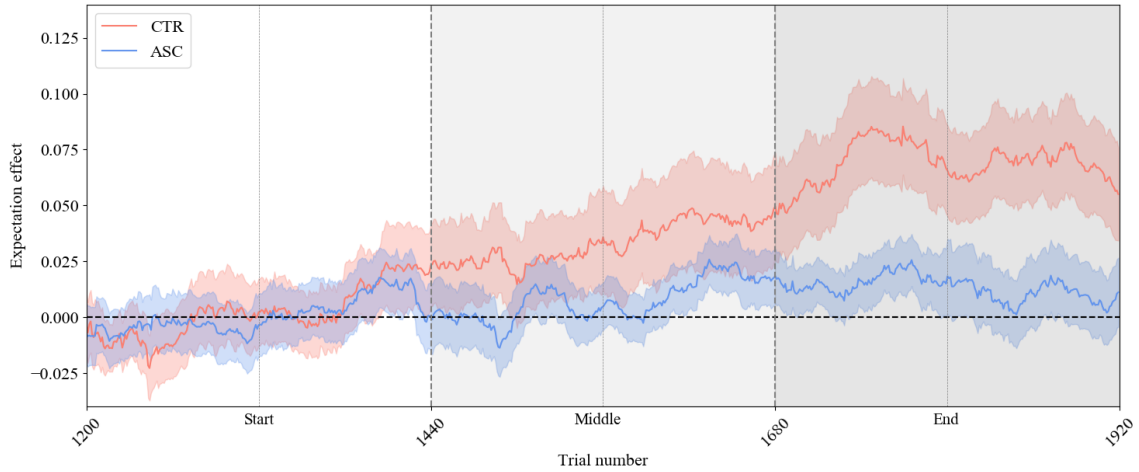
The results of the ANOVA found significant main effects of position ($F_{(2,114)} = 5.776$, $p = 0.004$), session ($F_{(1,57)} = 11.113$, $p = 0.001$) and group ($F_{(1,57)} = 4.766$, $p = 0.033$), and a significant position * group interaction effect ($F_{(2,114)} = 3.549$, $p = 0.032$). Non-significant interactions were found for session * group ($F_{(1,57)} = 2.291$, $p = 0.136$), position * session ($F_{(2,114)} = 0.448$, $p > 0.3$) and position * session * group ($F_{(2,114)} = 0.140$, $p > 0.3$).

A post-hoc comparison using pairwise t-tests (Bonferroni corrected) was carried out to further investigate the main effect of position. There was a significant increase in expectation effect between the start and end positions ($t(56) = -3.58$, $p = 0.002$), but not between the start and middle positions ($t(56) = -1.87$, $p = 0.200$) or the middle and end positions ($t(56) = -1.69$, $p = 0.291$). Full tables for the ANOVA and post-hoc analysis can be found in appendix A (tables A.3 - A.5)

The effect of position was then examined for each group independently. A one-way repeated measures ANOVA revealed a significant effect of position in the control group ($F_{(2,62)} = 7.058$, $p = 0.002$) but not in the autism group ($F_{(2,52)} = 0.282$, $p > 0.3$). Post-hoc analysis in the control group again revealed a significant increase in expectation effect between the start and end positions ($t(25) = -4.0$, $p = 0.001$), but not between the start and middle positions ($t(25) = -1.91$, $p = 0.198$) or the middle and end positions ($t(25) = -1.76$, $p = 0.263$). Full tables for the ANOVAs and post-hoc analysis can be found in appendix A (tables A.6 - A.8).



(a) First session



(b) Second session

Fig. 6.11 Trial-by-trial values for expectation effect during the first session (a) and second session (b) shown for the two groups. Expectation effect was calculated over a sliding window equivalent to the length of two blocks (240 trials). The solid line shows the group averages across trials for the control (red) and autism (b) groups and the filled areas show the standard errors. The thicker vertical dashed lines indicate the boundaries of the periods classified as the start (blocks 3 and 4), middle (blocks 5 and 6) and end (blocks 7 and 8). The thinner vertical dashed lines indicate the block boundaries.

6.4 Discussion

In this chapter, I used a probabilistic version of the serial reaction time task to assess whether autistic individuals were able to learn about underlying statistical regularities in the task and update their expectations when these regularities changed. The results indicated that autistic individuals showed a small but significant reduction in expectation effect across the task but there were no differences in the extent to which the two groups were affected by the reversal of probabilities. The significant main effect of the position variable demonstrated that participants were able to learn about the underlying structure of the task. The results showed a trend of increasing expectation effect from the start to end of each session, as expected, suggesting that participants were influenced more by their expectations as the task went on. This indicates that participants are able to learn complex regularities in a relatively short period of time. The structure of the underlying statistical regularities differed from the majority of serial reaction time tasks as it was non-deterministic, so this result provides novel insight to suggest that learning is still able to occur with increased levels of uncertainty.

The results also suggest that autistic individuals tended to show a reduced expectation effect compared to the non-autistic controls, as shown by the significant main effect of group. This indicates that, on average, autistic individuals tended to be influenced by their expectations to a lesser degree than the non-autistic controls. While this result is in contradiction to the wider literature (Barnes et al., 2008; Foti et al., 2015; Obeid et al., 2016; Zwart et al., 2017), it is important to highlight that the present study included a probabilistic reversal and so was distinct in its design to these previous studies. There was also a significant interaction effect between group and position, suggesting that the two groups showed differences in their rate of change of expectation effect across the task. The post hoc analyses indicated that control participants showed a difference between the start and end positions, but the autistic participants did not. This suggests that, across the 2 sessions, the autism group did not show a significant increase in expectation effect.

There was a significant main effect of session, which indicated that it was harder for participants to learn about the statistical regularities in the task following the probabilistic reversal. This was as expected, particularly due to the fact that the initial contingencies in the first session were non-deterministic and so participants may have initially perceived changes in the underlying structure during the second session to simply be statistical noise in the form of improbable trials. Previous studies had reported that autistic individuals experienced increased difficulties, relative to non-autistic controls, when required to update probabilities in reinforcement learning tasks (D'Cruz et al., 2013; Solomon et al., 2011; South et al., 2012). Based on this, I hypothesised that a similar effect would be found following reversals in the serial reaction time task. However, the absence of a significant interaction effect between the

session and group variables suggests there was a lack of evidence to show that the reversal had a stronger reductive effect on expectations in autistic individuals compared to control participants.

Before drawing any conclusions from the results, a number of considerations regarding the methodological validity should first be considered. Serial reaction time tasks have been criticised by some due to suggestions that the validity of whether they measure true implicit learning cannot be assessed as they don't include a means to detect awareness within the task (Hannula et al., 2005). However, such criticisms have been themselves been questioned due to the fact that they assume explicit and implicit learning are mutually exclusive. Instead, current understanding suggests that a continuum exists between the two types of learning which leads to a spectrum of levels of awareness during statistical learning tasks (Robertson, 2007). Nonetheless, it is not clear to what extent the information acquired during the task is done so implicitly or explicitly. Importantly, it is not clear whether the relative levels of explicit awareness during the task are similar between the control and autism groups.

Previous findings reported that, despite behavioural performance being similar between autistic and non-autistic participants, EEG recordings suggested that control participants tended to show a higher degree of incidental learning whereas autistic participants showed more effortful learning (Zwart et al., 2017). Therefore, it is a possibility that explicit awareness levels differed between the two groups during the task. This could be assessed in the future by adjusting the structure of the task so that participants are explicitly directed towards learning based on certain features while additional information is also presented within statistical regularities across other distinct features. This would allow for the comparison of implicit and explicit learning simultaneously (Robertson et al., 2004; Willingham et al., 2002). It is also possible to use analytic methods to assess awareness across a spectrum based on modelling significant changes in the reaction time distributions (Wessel et al., 2012), allowing for the relative effects of implicit and explicit awareness to be quantified during statistical learning tasks (Persaud et al., 2007). This approach could be considered in the future to clarify whether autistic and non-autistic participants show similar levels of awareness to the underlying statistical regularities.

Chapter 7

Acquisition of high-level information during sequential learning in autism

Overview

In this chapter, implicit awareness of statistical regularities was assessed using a serial presentation sequence followed by a two-alternative forced choice task. There were 3 unique versions of the task, in which the presentation and assessment of statistical regularities was done at either a low feature-based level or a high semantic-based level. The chapter aims to assess whether autistic individuals were able generalise across contexts when building statistical expectations of their environment.

7.1 Background

Building upon early findings that linked language development with auditory statistical learning (Saffran et al., 1996a, 1999, 1996b), a number of studies have also shown that statistical learning occurs in the visual domain (Fiser and Aslin, 2001, 2002a,b). This suggests that statistical learning is a domain-general mechanism (Kirkham et al., 2002) and that it may be one way in which prior expectations about our external environment are acquired (Seriès and Seitz, 2013a). These processes occur automatically (Turk-Browne et al., 2005) and are thought to be key in shaping language, reasoning and other aspects of cognition (Christiansen and Kirby, 2003). Statistical learning paradigms can be used to

create context-based associations and to build expectations of subsequent stimuli, which can increase perceptual attention to surprising (and therefore more informative) stimuli (Denison et al., 2016). These processes allow us to predict upcoming stimuli and influence perception based on the associations we have built up for the given context (as demonstrated in figure 7.1).

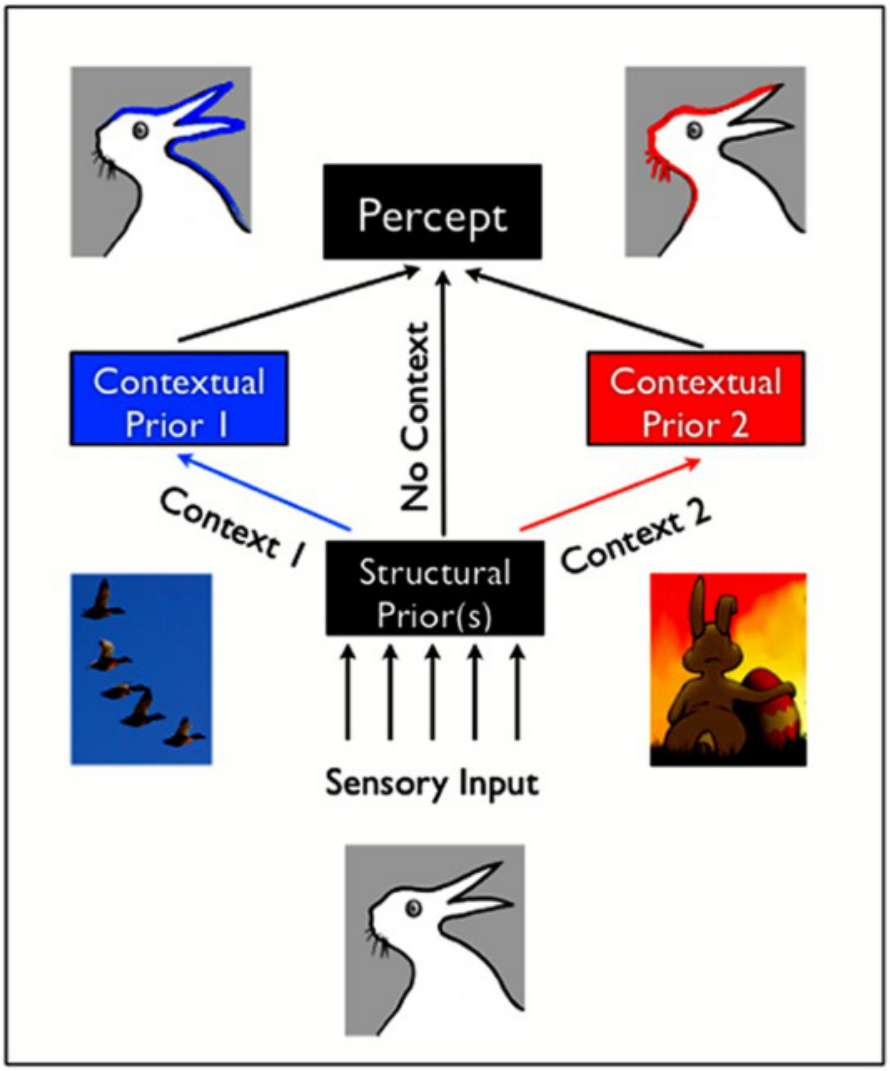


Fig. 7.1 An example of contextual expectations taken from Seriès and Seitz (2013a). In this figure, the bistable image of a duck/rabbit is influenced by context dependent expectations.

Early studies looking into visual statistical learning tended to assess learning using sets of abstract symbols (Fiser and Aslin, 2001, 2002b; Kirkham et al., 2002). More recently research has expanded on these early studies to assess whether statistical learning occurs when naturalistic scene images are used instead of symbol shapes (Brady and Oliva, 2008).

Scene processing is thought to be an important aspect of visual perception in day-to-day life. The recognition and categorisation of scenes is thought to involve the processing of feature-based statistics which help us to infer the type of scene we are viewing (Stansbury et al., 2013). However, the recognition of scene categories can in turn give the perceiver a useful context which can facilitate object recognition (Oliva and Torralba, 2007). Scene recognition is thought to occur at a similar level of abstraction to object recognition, rather than simply as the perception of the composite structure of objects within a scene (Konkle et al., 2010).

Brady and Oliva (2008) conducted a study that explored whether statistical learning would occur when using these 'real-world' stimuli sets. They carried out a number of experiments to assess whether predictive information occurring at higher-levels of abstraction could also be learned implicitly. They initially used images of different real-world scenes, such as pictures of buildings, mountains and forests, to assess whether participants could learn transitional contingencies between distinct images. After showing that their participants did indeed show robust effects of statistical learning of the transitional associations between these images, they included subsequent manipulations of the task to test whether participants were also able to learn predictive information when it occurred primarily at the semantic level. To do this, they presented participants with a sequence of images in which transitions between certain categories of images were more likely, but each individual image was only presented once. To show an effect of learning in this task, participants would have to implicitly extract statistical information at the level of the image categories. Not only did participants show an effect of learning in this version of the task, albeit to a lesser extent than in the initial task, but they also showed an effect of learning when their recall was tested using printed words for the different category types rather than image-based exemplars.

This finding, that semantic information can be acquired implicitly from scene images even when ges seqit is not relevant to the task being performed, has since been supported by subsequent studies (Goujon, 2011). The statistical regularities that occur across scene categories are thought to be processed at multiple levels of the visual systems hierarchical structure, acquiring information at both local and global levels (Jun and Chong, 2016). There is a body of evidence that shows that typically developed individuals are able to process and categorise the overall semantic content of scenes quickly but show limitations when detailed feature representation is required (Fabre-Thorpe, 2011). Based on reports of a tendency of autistic individuals to focus on low-level details to a greater extent (Happé and Frith, 2006; Koldewyn et al., 2013; Mottron et al., 2000; Plaisted et al., 1999), it is possible that these differences would affect how semantic information is processed during rapid serial presentation tasks such as the one presented by Brady and Oliva (2008).

While children with autism have been shown to be able to generalise statistical regularities in order to learn novel words (Haebig et al., 2017), there is an absence of any further investigation into whether autistic individuals are able to associate statistical contingencies with higher-level context and to generalise these associations to novel stimuli. Based on suggestions that generalisation may be a key deficit in autism (Plaisted, 2015) as well as specific claims of how this might be linked to a reduced influence of prior information (Van de Cruys et al., 2014), this area warrants further assessment. Further, as statistical learning tasks are an example of building and using prior expectations implicitly (Seriès and Seitz, 2013b) then the paradigm used by Brady and Oliva (2008) offers a way of testing the ideas of Pellicano and Burr (2012a) at different levels of abstraction. The aim of this chapter will be to assess whether autistic individuals are able to extract statistical information from image sequences of real-world scenes and whether this effect remains when the statistical regularities are presented at a semantic level.

7.2 Methods

7.2.1 Participants

A total of 125 participants took part in this study. This sample comprised of 61 participants with an autism diagnosis (44 males) and 64 non-autistic controls (45 males). All participants were right handed and had normal or corrected-to-normal vision. Participants with a diagnosis of an autism spectrum condition were recruited from the Cambridge Autism Research Database (CARD) and control participants were recruited from the Cambridge Psychology Volunteers Database or through classified adverts on websites such as Gumtree. There were no significant differences between the two groups on the proportion of males to females ($\tilde{\chi}^2(1) = 0.261, p > 0.3$), age (Control group, M = 30.01, SD = 7.76; Autism group, M = 32.18, SD = 8.40; $t(123) = 1.498$, $p = 0.13$) or IQ (Control group, M = 118.49, SD = 9.95; Autism group, M = 115.86, SD = 13.16; $t(123) = 1.274$, $p = 0.21$).

7.2.2 Stimuli

All stimuli were presented using the Psychtoolbox extension (Brainard, 1997; Kleiner et al., 2007) in MATLAB (MathWorks, 1989). The task involved presenting participants with various images of real-world scenes. These images were taken from 12 image sets of different scene categories (Konkle et al., 2010) [1]. Each set comprised of 68 images of scenes

[1] These stimuli are available from Timothy Brady's website (http://timbrady.org/stimuli.html)

belonging to specific categories. The 12 categories used in this study were: bathrooms, bedrooms, bridges, sky scrapers, coasts, fields, forests, kitchens, living rooms, mountains, roads, and waterfalls. Example images for each of the 12 different categories are shown in appendix B (figure B.2). Images were presented in the centre of the screen on a grey background (RBG: 127). All images subtended visual angles of 7.5 x 7.5. Participants were seated 60cm from a 24" monitor running at a resolution of 1920x1080.

7.2.3 Procedure

The task consisted of two distinct phases: a training phase and a recall phase. Participants were not informed that they would have to complete the recall phase until after they had finished the training phase. The instructions given at the start of the task referred only to the training phase and the instructions for the recall phase were only given to participants once the training phase was complete.

Training phase

Images of scenes were presented one after another for 300ms with a 700ms interval between images. Unbeknownst to participants, the images from the 12 different categories were randomly arranged into four subsets of three images (triplets). Images within triplets were always presented in a fixed order. The full sequence of images was created by randomly arranging 60 instances of each of the four triplets. The order was constrained so that the same triplet would never appear consecutively and so two triplets would not appear one after another twice in a row (i.e. XYXY would be forbidden, where X and Y represent triplets). All participants completed a total of 770 trials during the training phase. This comprised of 720 standard trials (which consisted of 60 presentations of each of the 4 different triplets) and 50 duplicate trials. Trials were presented across 5 blocks and participants were given a 60-second break between each block.

During the training phase, participants were instructed to respond by pressing the space bar when they saw back-to-back repeats of the same image (referred to as a duplicate). It was made clear to participants that they should only respond when they saw the image repeting on the trial that immediately followed the initial presentation. This cover task was utilized to increase attention to stimuli while both reducing the chance of participants becoming explicitly aware of the underlying sequence and providing a measure of attention during the task. To ensure the triplet structure was kept intact, only the first or third images in a triplet could be repeated. This procedure is demonstrated in figure 7.2.

Recall task

After the training sequence had finished, participants were then informed that they were going to be tested on the familiarity of various three-image sequences. During each test trial, one of the four triplets was presented alongside a foil triplet. Foil triplets were constructed by taking three images from three different triplets. Each of the four triplets was presented alongside each of the four foil triplets twice, with the order of presentation being counterbalanced. This gave a total of 32 trials that were presented in a random order. Each trial consisted of the images within the two triplets (genuine and foil) being presented with the same exposure and inter-stimulus intervals as the training phase. The two sequences (of the genuine and foil triplets) were separated by a 1000ms presentation of a fixation cross. After the genuine and foil triplets had both been presented, participants were then asked to respond to whether they thought the first or second sequence was more familiar by pressing the left or right keys.

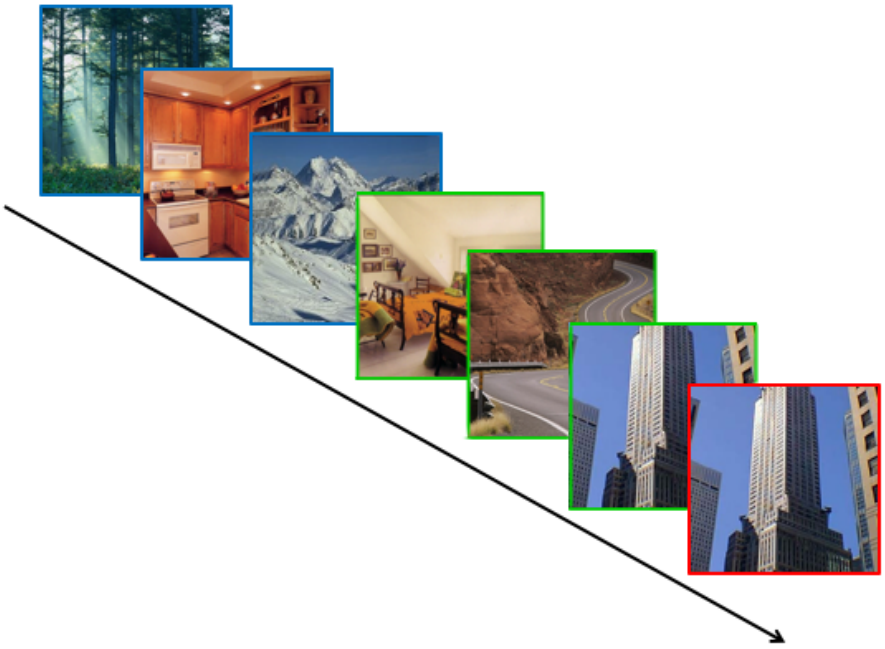


Fig. 7.2 Diagram showing an example sequence of images. Two separate triplets are shown, highlighted in blue and green respectively. A duplicate trial is demonstrated, highlighted in red.

7.2.4 Conditions

There were three versions of the task that participants were randomly assigned to. These versions of the task were the standard condition (referred to as *task A*), the category condition (referred to as *task B*) and the generalisation condition (referred to as *task C*). In the standard condition (task A) of the task, a single image was taken from each of the 12 different categories and used during the task. This meant that participants would see each of these 12 images a number of times and the transitional information (created by the triplet structure) was associated with specific images. For the category condition (task B), the whole set of images was used for each of the 12 categories and a unique image was used each time a category was represented. Therefore, each of the presentations of a triplet would comprise of three novel images but the category these images belonged to would stay constant (figure 7.3 shows an example of two instances of the same triplet in the category condition). This meant that participants would only see each individual image once and the transitional information was not associated with specific images but instead with category sets. Finally, the generalisation condition (task C) was a hybrid of the other two conditions. In this condition, participants were presented with a single image per category during the training phase (as in the standard condition) but were shown novel images during the recall phase (as in the category condition). This meant that participants would have been presented with the transitional information which was associated with specific images but were then tested on whether they also acquired transitional information associated with category sets.

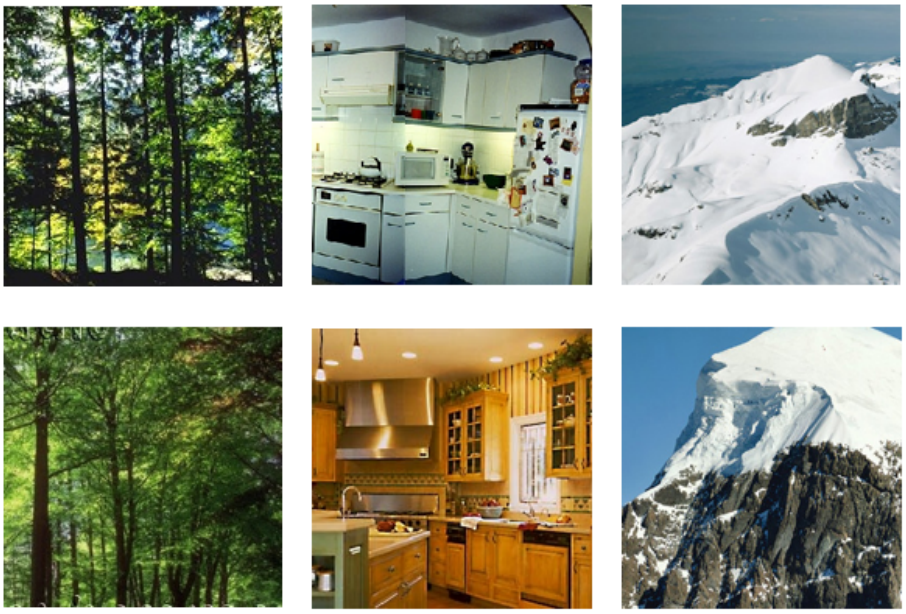


Fig. 7.3 Two examples of stimuli for the same triplet in the category-level condition. The triplet shown, forest - kitchen - mountain is the same as the blue triplet in figure 7.2.

7.2.5 Condition assignment

Each participant was assigned to one of the 3 different task conditions. 20 autistic participants (15 male) and 20 non-autistic participants (15 male) completed the standard condition of the task, 20 autistic participants (15 male) and 22 non-autistic participants (16 male) completed the category condition and 21 autistic participants (14 male) and 22 non-autistic participants (14 male) completed the generalisation condition.

Chi-squared tests were carried out on the frequencies of males and females across the two groups for each of the 3 task conditions. These were found to be non-significant for the standard ($\tilde{\chi}^2(1) = 0.0, p > 0.3$), category ($\tilde{\chi}^2(1) = 0.034, p > 0.3$) and generalisation conditions ($\tilde{\chi}^2(1) = 0.012, p > 0.3$), suggesting the ratio of male and female participants was balanced across the autism and control groups for all conditions. Similarly, there were no differences in the overall proportion of males and females ($\tilde{\chi}^2(2) = 1.197, p > 0.3$) or the proportion of autistic to non-autistic participants ($\tilde{\chi}^2(2) = 0.047, p > 0.3$) across the 3 conditions.

Participants in the 3 different conditions were also assessed for differences in age and IQ. There were no differences between the autistic and non-autistic participants in the standard condition (Age: $t(38) = 0.919$, $p > 0.3$; IQ: $t(38) = 0.426$, $p > 0.3$), the category condition (Age: $t(40) = 0.671$, $p > 0.3$; IQ: $t(40) = 0.195$, $p > 0.3$) or the generalisation condition (Age: $t(41) = 1.101$, $p = 0.277$; IQ: $t(41) = 0.275$, $p > 0.3$). There were also no overall differences

between the three conditions on either age ($F_{(2,122)} = 1.049$, $p > 0.3$) or IQ ($F_{(2,122)} = 1.055$, $p > 0.3$).

7.2.6 Data analysis

Training phase

Initial analysis of performance during the training phase was done using the proportion of correct responses across all trials in the training phase. Responses were coded as correct if there was a response during a duplicate trial or if these was an absence of a response in a non-duplicate trial. Responses were coded as incorrect if there was no response during a duplicate trial or there was a response during a non-duplicate trial. Scores were calculated as the proportion of the 770 trials in which the participant responded correctly.

The overall score is a relatively insensitive measure, as it fails to distinguish between errors that occur due to participants missing duplicates and errors that occur due to participants incorrectly responding during standard trials. To better capture response performance, a Signal Detection Theory (Harvey Jr et al., 1992) approach was used to assess the sensitivity and response criterion of participants responses during the training phase. This was done by treating trials in which duplicate images were presented as trials in which a 'signal' was present and all other trials as trials in which only 'noise' was present (Stanislaw and Todorov, 1999). The sensitivity, or discriminability index (d'), is a description of how discriminable the signal is from noise (or the absence of a signal). This can be defined as:

$$d' = \frac{\mu_S - \mu_N}{\sqrt{\frac{1}{2}(\sigma_S^2 + \sigma_N^2)}} \tag{7.1}$$

Where μ_S and σ_S are the mean and variance for responses in 'signal trials' and μ_N and σ_N are the mean and variance for responses in 'noise trials'. This can also be written as:

$$d' = Z(hit\,rate) - Z(false\,alarm\,rate) \tag{7.2}$$

Where Z(p) is the inverse of the cumulative distribution function of the given Gaussian distribution. It is also possible to calculate the response criterion, or response bias (C), which describes whether participants are biased towards over or under responding during the task. This can be expressed as:

$$C = -\frac{Z(hit\,rate) + Z(false\,alarm\,rate)}{2} \tag{7.3}$$

These two measures were calculated and used for a more detailed assessment of performance during the training phase.

Recall phase

Following the methods of Brady and Oliva (2008), performance during the recall phase was initially analysed using the proportion of correct responses across all trials. Responses were scored as correct if the participant correctly chose the true triplet and not the foil triplet. Single-sample t-tests were used to gauge whether the responses of participants across the groups as a whole were statistically different from chance guessing. Potential main effects of group and condition, as well as a possible interaction effect between the two variables, were tested for using a two-way ANOVA. The approach used by Brady and Oliva (2008) only assessed whether learning effects were present at the level of the group as a whole. I carried out an additional analysis to assess evidence for a recall effect at an individual level for each participant, using a Sequential Bayesian analysis (Schönbrodt and Wagenmakers, 2018).

The Sequential Bayesian analysis consisted of calculating the evidence in support of the presence of a true learning effect on a trial by trial basis for each participant. To do this, I evaluated the evidence for two alternative models: M_0, which assumes the participant is guessing and has a 50% chance of identifying the correct triplet, and M_1, which assumes the participant's responses tend towards an unknown value within the range of possible performance scores $p \in [0, 1]$. It is worth noting that the latter model was equally sensitive to participants who showed a bias towards incorrect identification as it is possible that implicit awareness of transitional contingencies could bias attention towards unfamiliar stimuli instead of familiar stimuli (Itti and Baldi, 2006).

Rather than using Bayes factors as a measure of evidence in support of the two models, as is traditionally done in such an approach (Schönbrodt and Wagenmakers, 2018), the ratio of the natural logs of the likelihood estimates for the two models were used. This was done to allow for comparable scaling for likelihood ratios in support of the null hypothesis model M_0 (where the equivalent Bayes factors would be $BF_{01} > 1$ or $BF_{10} < 1$) and likelihood ratios in support of the alternative hypothesis model M_1 (where the equivalent Bayes factors would be $BF_{10} > 1$ or $BF_{01} < 1$).

Log likelihood ratios were calculated in relation to M_1, so positive values represented evidence to support a recall effect and negative values represented evidence to support random guessing. Values with a magnitude above 2 are considered as *substantial evidence* in support of one of the two models and values above 6 are considered to be *strong evidence* (Kass and Raftery, 1995). Positive values show evidence in favour of model M_1, suggesting evidence to

support a recall effect, and negative values show evidence in favour of model M_0, suggesting evidence to support the absence of a recall effect.

It is also worth noting that, based on the relatively small number of trials, the model would not be able to confidently support the null hypothesis. A participant who was correct on exactly 50% of trials would yield a log likelihood ratio of -1.53 ($BF_{01} = 4.62$), which is considered to be *insignificant evidence* in support of the null. Whereas, if a participant were to correctly identify the triplet on every trial it would produce a log probability ratio greater than 10 ($BF_{10} > 150$), which would be considered very strong evidence in support of a recall effect. Therefore, the nature of the task means that it is not possible to have strong confidence for the true absence of a recall effect. Nonetheless, it allows for testing of whether there was evidence in favor of a recall effect to be assessed as the individual participant level.

7.3 Results

7.3.1 Training phase

Performance during the training phase was initially analysed using the proportion of correct responses across all trials in the training phase. The two groups were found to have equal variances ($F = 1.86$, $p = 0.175$) and a t-test indicated that the control participants ($M = 0.993$, $SD = 0.006$) and autistic participants ($M = 0.991$, $SD = 0.01$) did not significantly differ ($t(123) = 1.82$, $p = 0.071$). Group distributions and individual participant scores are displayed in figure 7.4.

A signal detection approach was then used to calculate the sensitivity and potential bias in participants responses (as detailed in the methods section). Scores for the sensitivity index (d') and decision criterion (C) were calculated for all participants and were compared across the two groups using t-tests. The two groups were found to have equal variances for both sensitivity index scores ($F = 0.44$, $p > 0.3$) and decision criterion scores ($F = 0.18$, $p > 0.3$). For the sensitivity index scores, the t-test found that the control participants ($M = 4.557$, $SD = 0.662$) and autistic participants ($M = 4.356$, $SD = 0.771$) did not significantly differ ($t(123) = 1.56$, $p = 0.121$). Similarly for decision criterion scores, the t-test showed that the control participants ($M = 0.637$, $SD = 0.214$) and autistic participants ($M = 0.620$, $SD = 0.231$) did not differ significantly ($t(123) = 0.45$, $p > 0.3$). These scores are displayed for all participants in figure 7.5.

Finally, an additional analysis was carried out to check there were no differences in performance during the standard training (where a single image was presented for each category type) and the category-level training (where a set of images was presented for each

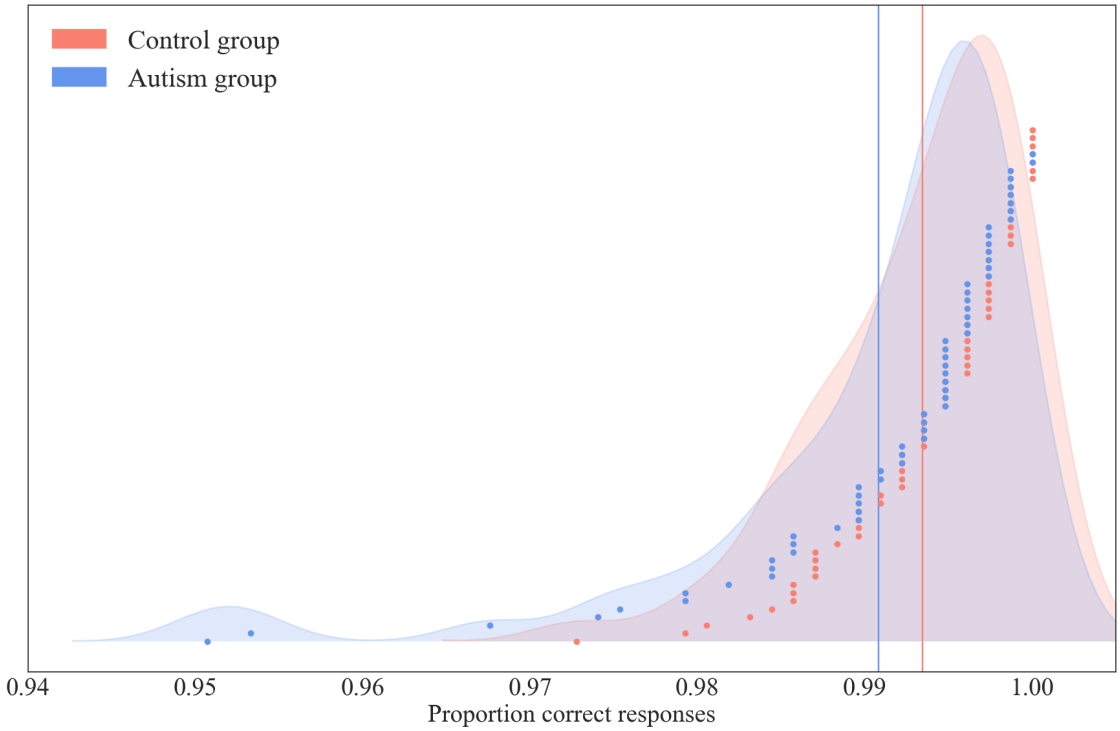
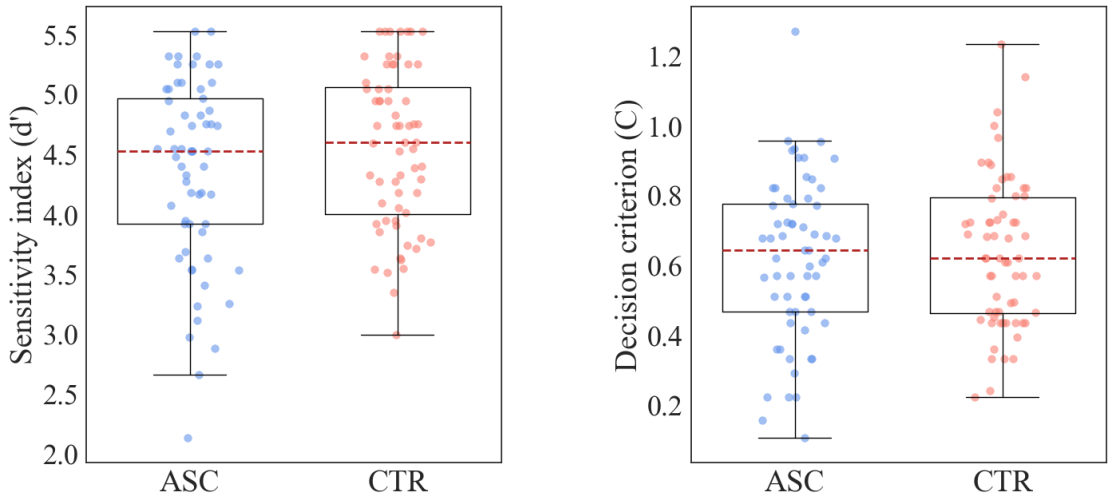


Fig. 7.4 Distributions of scores (proportion correct responses) in the training phase of the task. Distributions are shown separately for the two groups and individual data points are shown on top in ascending order from left to right. Group means are shown by the two vertical lines.

category type). This was done by assessing both the sensitivity index and decision criterion scores independently for each of the types of training. No significant differences were found between performance in the standard and category-level training tasks for either the control participants (d': $t(123) = 0.59$, $p > 0.3$; C: $t(123) = 0.47$, $p > 0.3$) or the autistic participants (d': $t(123) = 1.31$, $p = 0.198$; C: $t(123) = 0.60$, $p > 0.3$).



(a) Sensitivity index

(b) Decision criterion

Fig. 7.5 Box plots showing the signal detection performance measures during the training phase. Box plots are shown separately for the two groups (control: CTR and autism: ASC), for both the sensitivity index (a) and the decision criterion (b). Individual data from all participants are also displayed.

7.3.2 Recall phase

Performance during the recall phase was initially analysed using the proportion of correct responses across all trials. To assess whether performance during the recall phase was associated with the participants previous performance in the training phase, the correlations between the scores obtained in the two phases were calculated across all participants in each of the two groups.

Correlation with training phase

There was a small but significant correlation between the two performance measures within the control group ($r = 0.297$, $p = 0.020$). While this relationship failed to research significance in the autism group ($r = 0.210$, $p = 0.098$), a Fisher transform (Fisher, 1915) suggested that the relationship between performance in the training and recall phases did not significantly differ between the two groups ($Z = 0.51$, $p > 0.3$ *two-tailed test*). A scatter plot showing the associations between performance in the training and recall phases is displayed in figure 7.6.

To assess whether this relationship differed across the different condition types, correlations between performance in the training and recall phases were also examined after stratifying the data based on condition. There was a significant correlation between training

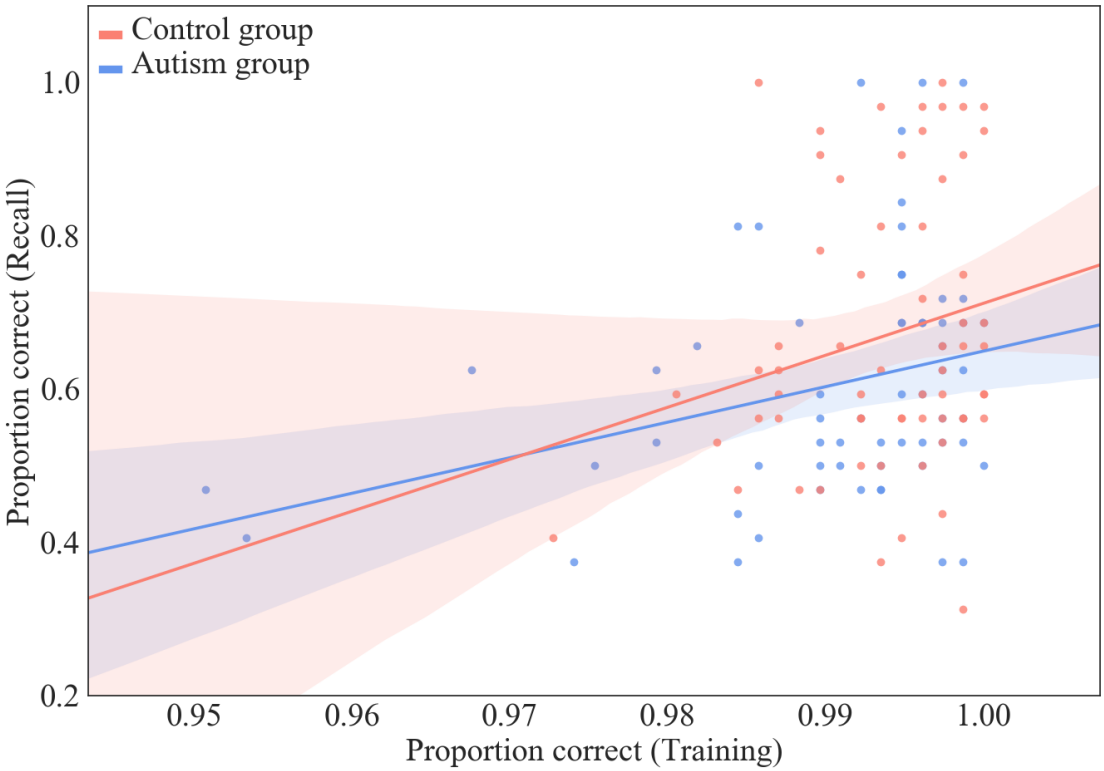


Fig. 7.6 Scatter plot showing the correlations between performance during the training phase and recall phase for both groups. Lines of best fit are shown for each group with the 95% confidence interval displayed by the shaded regions.

and recall performance in the standard condition ($r = 0.459$, $p = 0.003$) and the category condition ($r = 0.414$, $p = 0.006$). While the correlation in the generalisation condition failed to reach significance ($r = 0.245$, $p = 0.117$), Fisher transforms were carried out and found that the relationship between training and recall performance did not differ significantly between the generalisation condition and either of the other two conditions (Standard condition: $Z = 1.05$, $p = 0.294$ *two-tailed test*; Category condition: $Z = 0.81$, $p > 0.3$ *two-tailed test*).

Effects of group and condition on performance

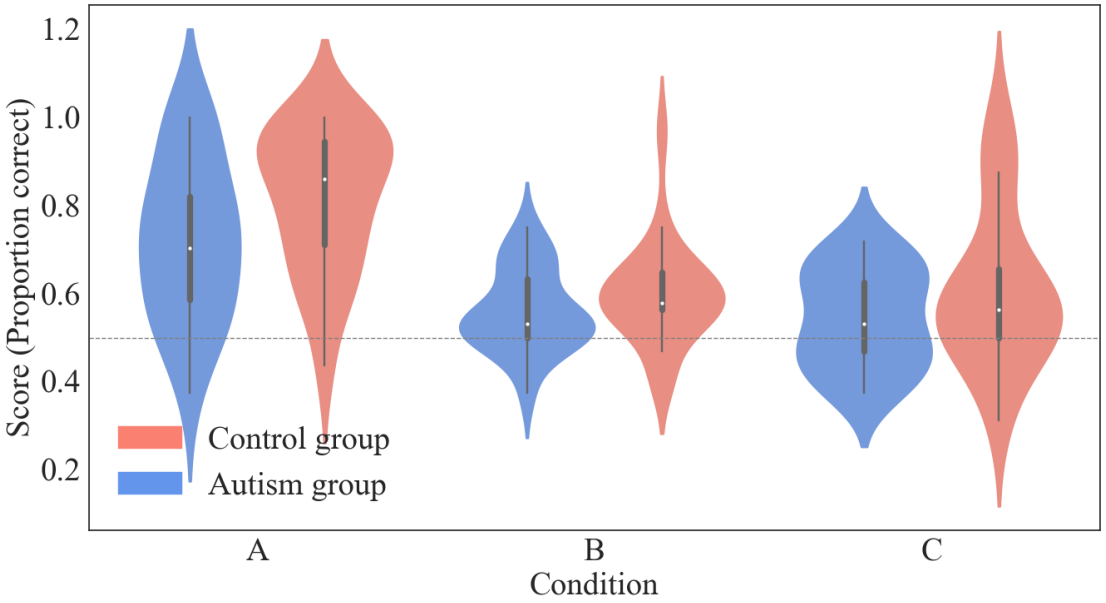
To assess whether there were differences in the extent to which the participants showed knowledge of the underlying statistics of the triplets, scores on during the recall phases was compared between participants in the two groups and across the 3 different conditions. Scores obtained by participants in both groups are shown across the different conditions in figure 7.7. The main effects of group and condition, as well as a potential interaction effect between the two variables, will be tested for using analysis of variance. However,

single-sample t-tests were carried out before conducting the main analysis to replicate the approach used by Brady and Oliva (2008). This was in order to gauge whether the responses of participants across the groups as a whole were statistically different from chance guessing. Initially, this was done by pooling all the participants together to test for learning effects in each of the 3 conditions.

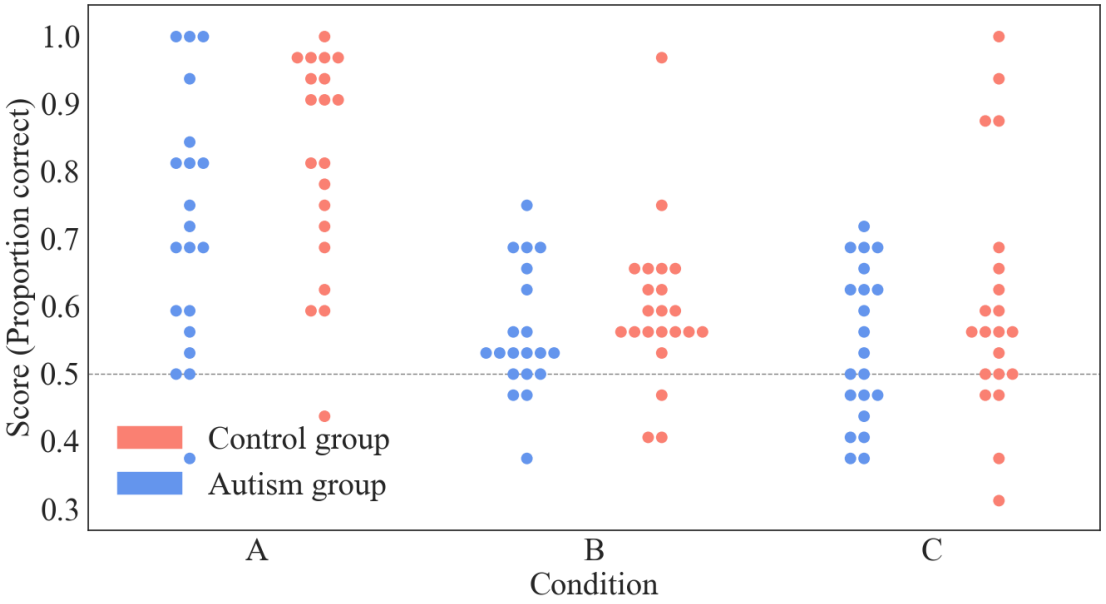
The generalisation condition was considered first, as it was not included in the study by Brady and Oliva (2008) and was therefore a novel condition. The performance of all participants that completed that condition of the task supported the case that there was a true learning effect ($t(41) = 3.22$, $p = 0.002$). Similarly, learning effects were found for the standard condition ($t(39) = 9.57$, $p < 0.001$) and the category condition ($t(41) = 4.88$, $p < 0.001$) as were previously reported in Brady and Oliva (2008). These effects were explored further by conducting additional one-sample t-tests for each of the two groups separately. In the standard condition, there was a significant learning effect for both the control participants ($t(19) = 8.74$, $p < 0.001$) and the autistic participants ($t(19) = 5.39$, $p < 0.001$). Similarly for the category condition, there were significant effects in both control group ($t(21) = 3.92$, $p = 0.008$) and autism group ($t(19) = 2.92$, $p = 0.009$). In the generalisation condition, there was a significant effect for the control group ($t(20) = 2.74$, $p = 0.013$) but not the autism group ($t(20) = 1.75$, $p = 0.095$). However, it is important to note that these one-sample t-tests were conducted to match the approach taken by Brady and Oliva (2008) and Bonferroni corrections were not applied.

To test for whether there were differences in performance across the different conditions and between the two groups, an analysis of variance was conducted. A two-way ANOVA was carried out with score (proportion correct) during the recall phase as the dependent variable and both task condition and group (diagnostic status) as between-subjects independent variables. The results of the ANOVA found significant main effects of condition ($F_{(1,118)} = 23.426$, $p < 0.001$) and group ($F_{(1,118)} = 6.148$, $p = 0.015$). Overall, control participants ($M = 0.669$, $SD = 0.181$) tended to identify the correct triplet in a higher proportion of trials than participants in autism group ($M = 0.607$, $SD = 0.155$). The interaction effect between condition and group was non-significant ($F_{(1,118)} = 0.413$, $p > 0.3$).

A post-hoc comparison was carried out using pairwise t-tests (Bonferroni corrected) to assess the main effect of condition. Scores in the standard condition ($M = 0.767$, $SD = 0.176$) were significantly higher than scores in both the category condition ($M = 0.580$, $SD = 0.106$; $t(80) = 5.89$, $p < 0.001$, *Cohen's d* = 1.303) and scores in the generalisation condition ($M = 0.575$, $SD = 0.151$; $t(80) = 6.01$, $p < 0.001$, *Cohen's d* = 1.170). Scores in the category and generalisation conditions did not significantly differ from one another ($t(80) = 0.114$, $p >$



(a) Violin plots



(b) Individual data points

Fig. 7.7 Scores in the recall phase (proportion correct) stratified by group and condition type. Distributions are shown as violin plots (a) and as individual data points (b). The expected score based on chance guess (0.5) is shown as a horizontal grey dashed line.

0.3, *Cohen's d* = 0.028). Full tables for the ANOVA and post-hoc analysis can be found in appendix A (tables A.9 and A.10).

Recall effect at the participant level

A Sequential Bayesian analysis (Schönbrodt and Wagenmakers, 2018) was carried out across each participants' set of responses in the recall phase, as detailed in the methods section. The final log likelihood ratios obtained at the end of the recall phase are shown for all participants in figure 7.8. The different levels of evidence strength (as suggested by Kass and Raftery (1995)) are also indicated on the figure. The results show that moderate or higher evidence was found to support a learning effect in 20 of the 63 control participants (14 of which were in the standard condition, 2 in the category condition and 4 in the generalisation condition). For the autism group, 10 of the 61 participants gave responses that provided a moderate or higher evidence to support a learning effect (9 of which were in the standard condition and 1 in the category condition). These relative proportions of participants for which there was at least moderate evidence of a learning effect were then compared between the two groups using a Chi-squared test, however this failed to reach significance ($\tilde{\chi}^2(1) = 3.19, p = 0.074$). The average paths for the sequential accumulation of evidence from participant responses are shown in figure 7.9.

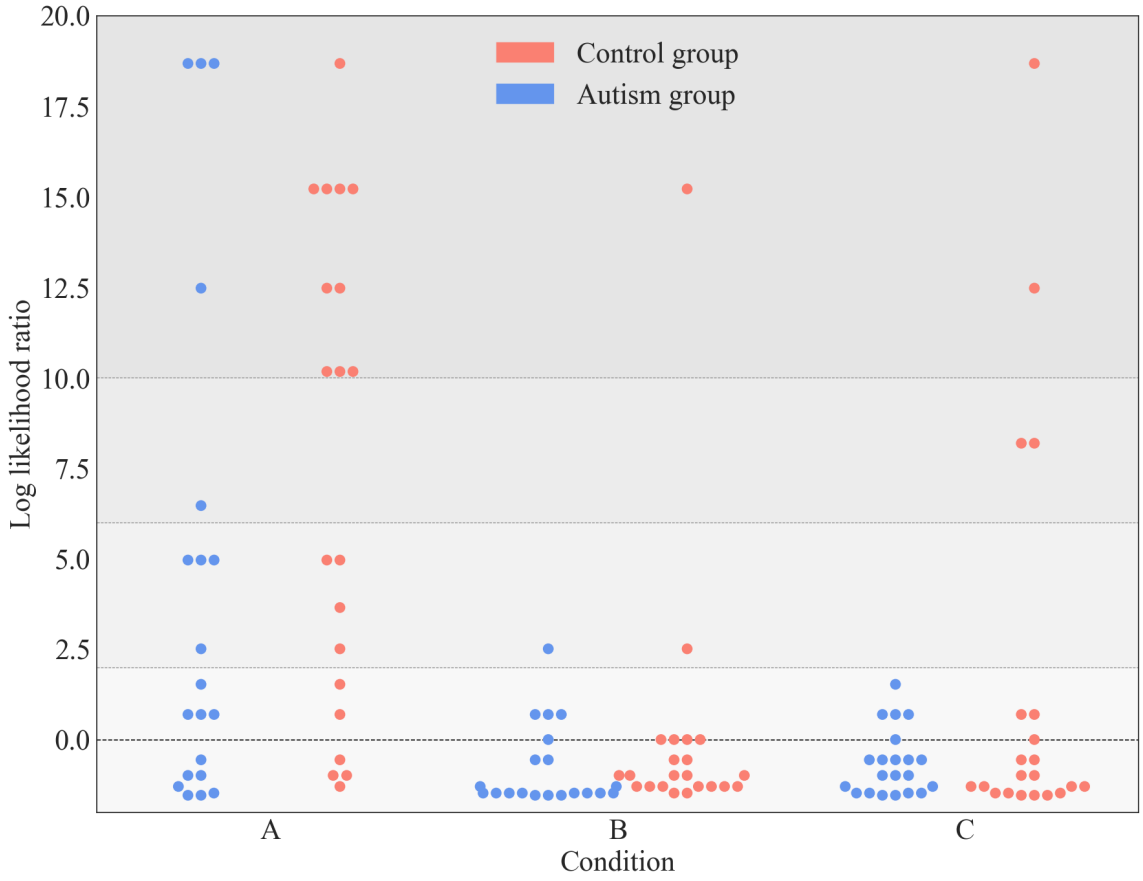


Fig. 7.8 Log likelihood ratios after all trials in the recall phase for each participant. Ratios are stratified by group and condition type. Suggested boundaries for different evidence levels are indicated by the dashed lines. The different regions represent 'insignificant evidence', 'positive evidence', 'strong evidence' and 'very strong evidence', with increasingly dark shading representing increasing levels of evidence (Kass and Raftery, 1995).

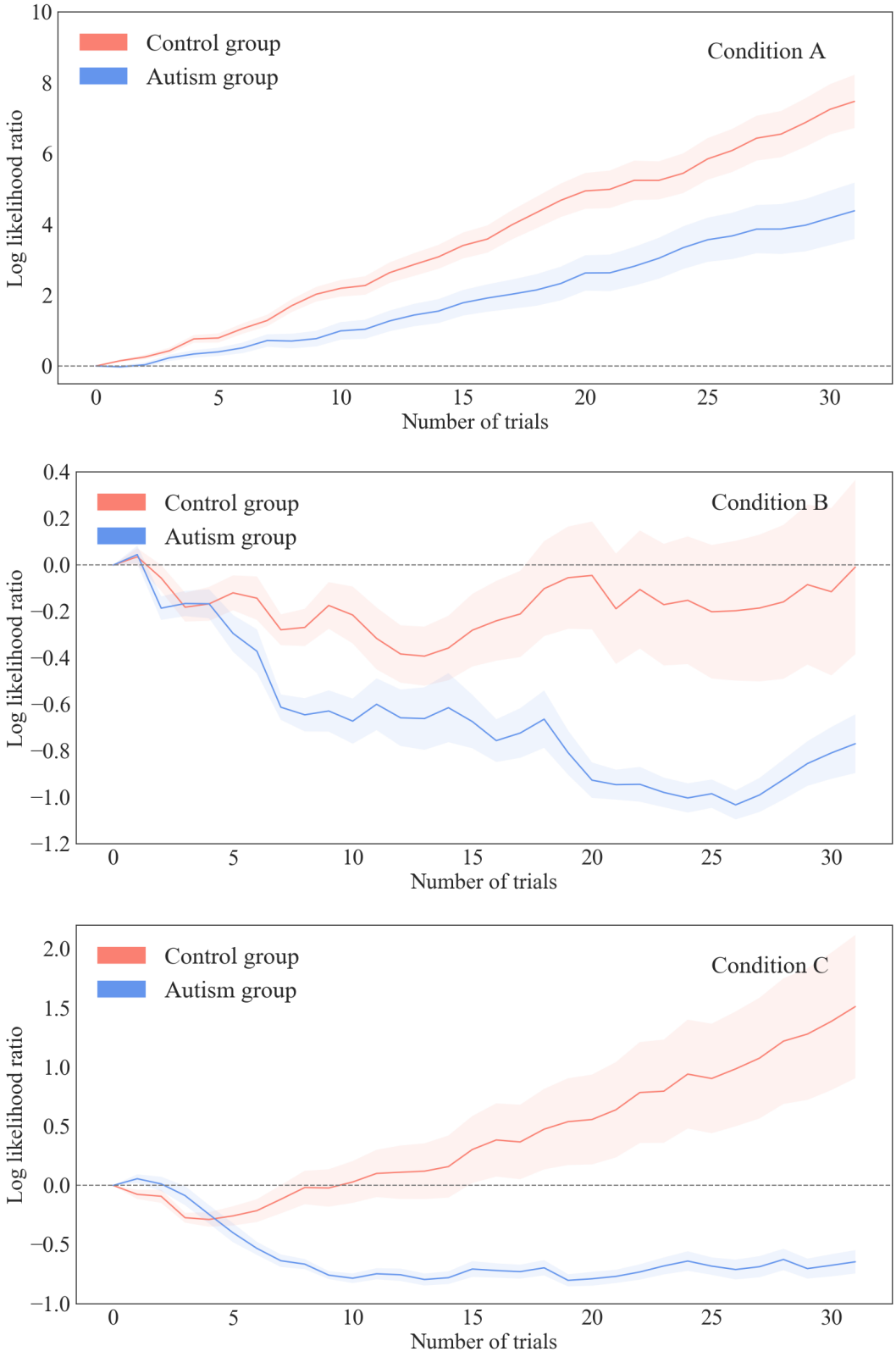


Fig. 7.9 A plot of the average outcome on the log likelihood ratio as data is collected across all trials of the recall phase. Data are shown for each of the three conditions, with separate averages for the two groups. Standard errors are shown by the shaded regions. Positive values indicate that, on average, participants were considered to have shown responses that were more likely to occur based on the alternative hypothesis model (M_1, the existence of a recall effect). Negative values indicate that participants showed responses that were more likely to occur based on the null hypothesis model (M_0, the absence of a recall effect).

7.4 Discussion

The results presented in this chapter found that the autism group showed a modest but significant reduction in performance during the recall phase when compared to the non-autistic controls. This result was only present when data were considered across all 3 conditions of the task and this should be considered when interpreting the findings of this study. As no interaction effect was found between the group and condition variables, there was no evidence to suggest that the autism group showed any specific difficulties in processing information at the category level or generalising information at this level. This suggests that the results do not support the hypotheses that autistic individuals may experience difficulties in acquiring statistic regularities at higher-levels or difficulties in generalising prior expectations across different contexts.

The findings presented in this chapter suggest that autistic individuals extracted less information during the training phase than the non-autistic controls. This result is distinct from the findings of chapter 6, as the effects of learning were assessed through a forced choice paradigm. The results from the serial reaction time task did not necessarily indicate that autistic individuals showed reduced learning of the statistical regularities of the task, but rather that autistic individuals' performance on the task was influenced by their prior experiences of the task to a lesser extent. While it is possible that this could be due to autistic individuals not learning about the underlying probabilities to the same extent as the non-autistic controls, it is also possible that learning was similar between the two groups but the autistic individuals relied on this prior information to a lesser extent during the task. Therefore, the results from the present chapter are a novel finding in addition to those from the serial reaction time task.

This interpretation of these results does, however, rest on the assumption that the approach used in the recall phase accurately captures the level of learning that occurred in the training phase. A 2-alternative forced-choice (2AFC) paradigm was used to assess participants memory for triplets in the recall phase (Green and Swets, 1966). There are some criticisms of the 2AFC approach that suggest order effects can influence participants responses, however these are more problematic when testing for perceptual sensitivities rather than recall (García-Pérez and Alcalá-Quintana, 2011). An alternative method for assessing recall is the yes/no paradigm (Ahumada Jr and Lovell, 1971), however this approach could potentially be probematic when comparing autistic and non-autistic individuals due to differences in the interpretation of the task which could result in biases (Hauck et al., 1998). Broadly speaking, there are a number of issues that can occur with explicit test phases at the end of implicit learning tasks, such as large amounts of noise when averaging across participants due to chance guessing and less power to detect true effects due to insufficient numbers of trials

(Siegelman et al., 2017). Nonetheless, when considered alongside the results from the serial reaction time task, the present finding seems to suggest that autistic individuals extract predictive information from their environment to a lesser extent than non-autistic individuals.

It is also important not to assume that the learning effects found in the category and generalisation conditions were based on semantic information, as it is possible that the higher levels of correlation between low-level features within same-category images compared to different-category images led to the observed recall effects (Stansbury et al., 2013). While, Brady and Oliva (2008) carried out experiments specifically to show that semantic information was processed during the task, this does not necessary extend to the sample in the present study. Indeed, it is a possibility that the two groups showed similar recall effects while actually processing different levels of information within the task. This possibility could be clarified by the inclusion of a word-based recall phase, as was included in the original study by Brady and Oliva (2008). However, the present study was unable to include this due to the additional demand on data collection that the inclusion of further conditions would have resulted in. An alternative approach would be to assess whether within-category correlations of low-level features accounted for variation in the observed memorability of the different categories and, if so, whether this effect differed between the two groups (Khosla et al., 2015, 2012; Squalli-Houssaini et al., 2018). This could be explored in future studies to build a more complete picture of the level at which autistic and non-autistic individuals process category-level information.

Part IV

Psychometric assessment

Chapter 8

Psychometric assessment of the autism phenotype

Overview

This chapter introduces a number of different questionnaire measures that have previously been associated with autism or an intolerance towards uncertainty. The characteristics of a large sample of autistic and non-autistic individuals are described across these various measures. Potential confounding effects of age and sex are also taken into consideration.

8.1 Background

Difficulties with uncertain or unstable situations and environments have been a long-standing feature of autism. An association of autism with an "insistence of sameness" can be traced back to Leo Kanner's first reports of the condition (Kanner, 1943). Indeed, insistence on sameness is a criterion within diagnostic tools such as the Autism Diagnostic Interview (Lord et al., 1994; Rutter et al., 2003) and the DSM-5 (DSM-5 American Psychiatric Association, 2013). This drive towards sameness and stability can also be framed as an aversion to uncertainty or instability, with similar results stemming from measures of these two constructs and many studies using the terms 'insistence of sameness' and 'intolerance of uncertainty' interchangeably (Black et al., 2017; Boulter et al., 2014; Neil et al., 2016; Uljarević et al., 2017).

Such difficulties with processing uncertainty and ambiguity are in line with recent accounts that suggest predictive processes might be disrupted in autistic individuals (Gomot and Wicker, 2012; Lawson et al., 2014; Pellicano and Burr, 2012b; Sinha et al., 2014). Challenges with processing information in unpredictable environments may lead to autistic individuals being averse to uncertain situations and actively avoiding unfamiliar contexts by maintaining familiar routines. This is summed up in a quote by Dora Raymaker, the director of the Academic Autistic Spectrum Partnership in Research and Education. She says that:

> "The experience of many of us is not that "insistence on sameness" jumps out unbidden and unwanted and makes our lives hard, but that "insistence on sameness" is actually a way of adapting to a confusing and chaotic environment..."
> *Dora Raymaker, taken from Sinha et al. (2014).*

Further, it may be that this pursuit of sameness is driven specifically by the anxiety that occurs from uncertain environments. Deborah Lipsky, a board member of the Autism Society of Maine, describes how she seeks to control and regulate her environment due to anxiety around uncertainty:

> "I can't emphasize enough how critical it is to understand that staying on a script is the sole means of keeping anxiety at a minimum. Even the smallest breach becomes a crisis because all we register at that moment is unpredictability. We fear unpredictability above all else because we are out of control of our environment." *Deborah Lipsky, taken from Lipsky (2011).*

Research has recognised the importance of 'intolerance of uncertainty' as a psychological construct, defining it as negative attitudes towards processing and acting on uncertain situations (Buhr and Dugas, 2002). This construct is commonly measured using the Intolerance of Uncertainty Scale (Birrell et al., 2011; Freeston et al., 1994). Recent research has made use of this measure to empirically show that autistic individuals show elevated levels of intolerance of uncertainty (Boulter et al., 2014; Chamberlain et al., 2013; Maisel et al., 2016; Neil et al., 2016). These studies have also explored how intolerance of uncertainty interacts with other known features of autism such as sensory issues and heightened anxiety levels. Previous research has also used other questionnaire measures alongside the Intolerance of Uncertainty Scale to build an understanding of how variability within an individual's degree of intolerance of uncertainty can be predicted by other distinct features of autism. Vasa et al. (2018) used questionnaire data from autistic children and non-autistic controls to build a linear regression model of intolerance of uncertainty. Their model showed that intolerance

of uncertainty could be predicted by diagnostic status as well as features such as repetitive behaviors, social communication deficits, emotional dysregulation and anxiety.

The large majority of studies which have looked at intolerance of uncertainty in autism are conducted on younger populations, predominantly children and adolescents. Typically, autism studies that focus on clinical features and interventions tend to involve younger populations as it can be argued that early interventions are the most effective for targeting clinical features such as anxiety (Fox et al., 2012; Hudson, 2017). However, a better understanding of how the clinical features of autism might manifest themselves specifically in adults is equally important considering the high number of individuals that are not diagnosed until later on in adulthood (Lewis, 2017), particularly in females (Wilson et al., 2016).

The motivation for this section of the thesis was to collect a large amount of questionnaire data from both autistic and non-autistic adults that could be used to explore how the construct of intolerance of uncertainty manifests itself in autistic individuals. This section comprises of 3 experimental chapters which focus on data obtained using the Intolerance of Uncertainty Scale alongside questionnaire measures of other clinical and behavioural features of autism. First, in this chapter I will look for group differences in the scores obtained by autistic and non-autistic individuals on a number of questionnaire measures. In the subsequent chapter I will then take a similar approach to Vasa et al. (2018) by using regression models to explore which of the other features associated with autism were predictive of intolerance of uncertainty. This will build upon the results of the first chapter by including terms for all measures that were associated with autism as well as an interaction terms with sex or age. Finally, in the final chapter of this section I will assess whether I'm able to find similar effects in an adult sample to those that were reported in previous studies that found a mediating role of intolerance of uncertainty in the relationship between autism and other features, such as sensory issues and anxiety, in autistic children (Boulter et al., 2014; Neil et al., 2016).

The first step of this section was to analyse questionnaire data from a number of different measures to determine which of these were associated with autism and whether there were any interactions with possible covariates such as participants' sex or age. This chapter will focus on carrying out a detailed descriptive analysis of each questionnaire measure within a large online sample of autistic and non-autistic individuals.

8.2 Methods

8.2.1 Participants

A total of 696 participants took part in the study. Recruitment was carried out through multiple mediums. The primary method of recruitment was through the Cambridge Autism Research Database (CARD). This is a database that allows volunteers to register online (www.autismresearchcentre.com) and provide details about themselves and their diagnosis. Volunteers on the database were contacted through a mailing list and were provided with a link to the study instructions and questionnaire measures. A total of 406 participants were recruited through the CARD database. Additional participants were recruited via social media websites such as Twitter (N=102), Facebook (N=76), Reddit (N=55) as well as through university newsletters (N=57). There was no direct reimbursement for taking part in this study but 4 prizes of £50 were offered via a prize draw from all the participants that took part in the study. Within the sample, there were 317 (male = 123, female = 194) who reported a diagnosis of an autism spectrum condition and 239 (male = 58, female = 181) that reported not having a diagnosis of an autism spectrum condition.

8.2.2 Measures

Autism Spectrum Quotient

The Autism Spectrum Quotient (AQ) is a 50-item questionnaire that assesses an individual's degree of autistic traits (Baron-Cohen et al., 2001). The AQ includes questions evaluating both social and non-social domains and examines behaviour, cognition, ability, and a number of preferences in a brief, self-administered, forced-choice format. Items are in the form of statements and participants are asked to respond based on how much they agree with each item. Responses were taken using a 4-point Likert scale with possible options of "definitely agree", "slightly agree", "slightly disagree", and "definitely disagree". A binary system is used for scoring, where agreement with autistic-like behaviour is scored as a 1 and disagreement is scored as a 0. This leads to a maximum possible score of 50. The questionnaire includes 26 positively worded items and 24 reverse worded items for which scoring is adjusted appropriately. The AQ has been shown to have good test-retest reliability and high internal consistency and scores in autistic individuals are significantly higher than scores in non-autistic controls (Baron-Cohen et al., 2001).

Empathy Quotient

The Empathy Quotient (EQ) consists of 40 items each of which can be scored as either 0, 1 or 2, giving a maximum possible score of 80 (Baron-Cohen and Wheelwright, 2004). Responses were taken using a similar Likert scale to the AQ. The questionnaire is designed to characterise the degree to which an individual is affected by others' emotions and their ability to gauge and understand the emotions of others. 21 items are worded so that high levels of empathy would be expected to produce an "agree" response and the other 19 items are worded so that high levels of empathy would be expected to produce a "disagree" response. Scores on the EQ have been shown to be significantly lower in autistic individuals than in non-autistic controls (Baron-Cohen and Wheelwright, 2004).

Systemising Quotient-Revised

The Systemising Quotient-Revised (SQ) consists of 75 items each of which can be scored as either 0, 1 or 2, giving a maximum possible score of 150 (Baron-Cohen et al., 2003). Responses were taken using a similar Likert scale to the AQ and EQ. The questionnaire gauges an individual's drive to analyse or construct systems. 36 items are worded so that high levels of systemising would be expected to produce an "agree" response and the other 39 items are worded so that high levels of systemising would be expected to produce a "disagree" response. Scores on the SQ have been shown to be significantly higher in autistic individuals than in non-autistic controls and have also shown to be elevated in individuals with a background in science or mathematics (Baron-Cohen et al., 2007; Billington et al., 2007; Bressan, 2018).

Glasgow Sensory Questionnaire

The Glasgow Sensory Questionnaire (GSQ) is a 42-item questionnaire that assesses abnormal sensory behaviours (Robertson and Simmons, 2013). Responses to each item are based on a 5-point Likert scale with possible answers of "Never", "Rarely", "Sometimes", "Often" and "Always". These responses are scored from 0-4 points respectively giving a maximum possible score of 168. Scores on the GSQ have been shown to correlate strongly with autistic traits within the non-autistic population (Robertson and Simmons, 2013) and autistic individuals have been shown to score higher than non-autistic controls (Ward et al., 2017).

Zung Self-rating Anxiety Scale

The Zung Self-rating Anxiety Scale (ZAS) is a 20-item questionnaire that assesses both affective and somatic anxiety symptoms. Each item contains a statement about a type of

experience and participants are asked to respond to how often this occurs for them using a 4-point Likert scale with possible answers of: "A little of the time", "Some of the time", "Good part of the time" and "Most of the time". 15 items express a negative experience and the other 5 items express a positive experience and are reverse scored. Items can be scored from 1 to 4, giving a maximum possible score of 80. A raw score of 36 is suggested as a cut-off point for clinically significant anxiety (Zung, 1980). Previous studies have shown the measure to have good internal consistency (Tanaka-Matsumi and Kameoka, 1986).

Toronto Alexithymia Scale-II

The Toronto Alexithymia Scale-II (TAS) is a 20-item questionnaire that measures alexithymia, difficulties in identifying and describing one's own emotions (Bagby et al., 1994). Participants are required to rate how much they agree with various statements using a 5-point Likert scale with possible answers of "Strongly Disagree", "Moderately Disagree", "Neither Disagree Nor Agree", "Moderately Agree" or "Strongly Agree". Each item is scored 1 to 5, giving a maximum possible score of 100. Scores that exceed 60 points are considered to indicate high levels of alexithymia (Bermond, 2000). The measure has been shown to have good reliability and factorial validity (Taylor et al., 2003; Wise et al., 2000). Scores on the TAS have been shown to correlated with autistic traits as well as being increased in autistic individuals (Cook et al., 2013; Shah et al., 2016).

The Obsessive-Compulsive Inventory-Revised

Obsessive-Compulsive Inventory-Revised (OCI) (Foa et al., 2002) is an 18-item questionnaire which measures a number of symptoms associated with Obsessive Compulsive Disorder including checking, ordering, hoarding and obsessions. Participants are asked to rate the degree to which they have been affected by different symptoms during the past month using a 5-point Likert scale. Possible responses for each item are: "Not at all", "A little", "Moderate", "A lot" and "Extremely" which are scored from 0 to 4, giving a maximum possible score of 72.

The Intolerance of Uncertainty Scale

The Intolerance of Uncertainty Scale (IUS) is a 12-item questionnaire which measures the degree to which an individual holds negative attitudes towards uncertainty. The questionnaire consists of 27 statements about uncertainty where participants are asked to rate how characteristic they think the statement is of them. Each item can be scored from 1 to 5, where 1 indicates the statement is "Not at all of me" and 5 indicates the statement is "Entirely

characteristic of me", giving a maximum possible score of 135 (Buhr and Dugas, 2002; Freeston et al., 1994). Scores on the IUS have been shown to be significantly higher in autistic adults than in non-autistic controls (Maisel et al., 2016).

8.2.3 Data cleaning

Missing characteristics data

Participants were removed if they failed to report either their diagnostic status, their sex or their age. Control individuals were excluded if they reported a suspected diagnosis or that they had previously sought a diagnosis or planned to seek one in the future. In total, 142 participants were removed from further analyses due to these exclusion criteria. Participants who had completed the questionnaires multiple times were identified (11 participants across 23 sets of responses) and only one set of their responses was included in the final sample. Selection of which response set to include was done firstly by determining which response set was the most complete and then, if two responses sets had equal levels of completion, by selecting the first response set in terms of ascending date of completion. Overall, 12 sets of responses were removed due to being duplicate responses.

Missing questionnaire data

For each questionnaire measure, participants were required to complete all question items in order to progress on the online questionnaire. This meant that there was no missing data within completed questionnaires.

Response quality

Additional steps were taken to attempt to identify participants who gave overly repetitive response as these can be a marker of careless, low-effort responses (Huang et al., 2012). However, identifying and removing extreme responses as outliers can lead to an increase in Type 1 error rates (Bakker and Wicherts, 2014) and may lead to the removal of individuals who represent the higher and lower ends of the natural range of the traits being measured.

A number of the questionnaire measures used in the present study included reverse-scored questionnaire items. These items can be used to identify instances in which participants have a high level of inattention or may be showing an acquiescence response bias (Lavrakas, 2008). In order to remove such participants, I quantified the level of response variation by calculating the level of response entropy for all participants. This was done by using the respective frequency of each response option to calculate probability values for each

participant based on their individual likelihood to give specific responses. Response entropy values were then calculated using the standard formula for informational entropy:

$$H(X) = -\sum_{i=1}^{n} P(x_i) log_2 P(x_i) \tag{8.1}$$

A cut off value was defined by calculating the entropy value for simulated participant data where consistent responses were given across all forward-score items and distinct but consistent responses for reverse-coded items. For example, for the AQ questionnaire there were 4 possible response options across 26 forward-coded items and 24 reverse-coded items. The entropy cut off value for this questionnaire would be calculated as follows:

$$H(X) = -P(x_1) log_2 P(x_1) - P(x_2) log_2 P(x_2) - P(x_3) log_2 P(x_3) - P(x_4) log_2 P(x_4) \tag{8.2}$$

$$\begin{aligned} H(X) = &-P(\frac{26}{50}) log_2 P(\frac{26}{50}) - P(\frac{24}{50}) log_2 P(\frac{24}{50}) \\ &-P(\frac{0}{50}) log_2 P(\frac{0}{50}) - P(\frac{0}{50}) log_2 P(\frac{0}{50}) \end{aligned} \tag{8.3}$$

$$H(X) = -(-0.490) - (-0.508) - 0 - 0 = 0.998 \approx 1 \tag{8.4}$$

Where x_1 - x_4 are the possible responses. The maximum entropy for responses across the questionnaire can be calculated by assuming that a participant is equally likely to give any of the 4 responses for any given answer. This would give:

$$H(X) = -P(\frac{1}{4}) log_2 P(\frac{1}{4}) - P(\frac{1}{4}) log_2 P(\frac{1}{4}) - P(\frac{1}{4}) log_2 P(\frac{1}{4}) - P(\frac{1}{4}) log_2 P(\frac{1}{4}) \tag{8.5}$$

$$H(X) = -(-0.5) - (-0.5) - (-0.5) - (-0.5) = 2 \tag{8.6}$$

These calculations represent an estimate of the average entropy for each individual question item. The overall entropy across the entire questionnaire could be calculated by multiplying average entropy per questionnaire item by the number of individual questionnaire items. However, this is not required in this instance. For the results presented here, an additional 5% of variation in responses was included when calculating the response entropy cut off values. The AQ, EQ and SQ were the 3 questionnaire measures used to assess

response entropy as they all included reverse-items and had a satisfactory number of items for the analysis. For all 3 measures, the cut off value used for removing participants was $H(X) = 1.25$.

8.2.4 Descriptive analysis

Descriptive analyses were carried out across the 8 questionnaire measures. This was done to establish the characteristics of the participant responses for each of the measures within the sample. For each of the measures, analyses were conducted to established:

- If the overall scores were normally distributed across the whole sample.
- Whether overall scores differed between the autism and control groups.
- Whether sex had an effect on overall scores and, if so, whether this sex had an interaction effect with diagnostic status.
- Whether overall scores correlated with age.

The descriptive analyses will allow me to determine which of the questionnaire measures were sensitive to aspects of the autism profile. Measures which are found to detect significant group differences between the autism and control groups will be included in subsequent analyses to explore the nature of intolerance of uncertainty as a construct and also to investigate possible mediating roles between these different measures. Additionally, the descriptive analyses will allow me to establish whether there are differences in age and the sex-ratio between the two clinical groups. If this is the case, then steps will be taken to control for the influence of age and sex in order to assess whether a true effect of diagnostic status exists across the difference questionnaire measures.

As the main analysis would focus on effects of diagnostic status, it was important to test for interactions between sex and diagnostic status as well as main effects of sex. Two-way between-subjects ANOVAs were conducted for each of the 8 questionnaire measures as the outcome variable. In each analysis, diagnostic status, sex and diagnosis * sex were included as factors. A Bonferroni correction was used to account for multiple testing across the 8 different measures. Results are reported within the main descriptive analysis section.

8.3 Results

8.3.1 Response quality

Entropy cut-off values were calculated for the AQ, EQ and SQ. Participants whose response entropy fell below the cut-off value for at least one of the 3 measures were removed from further analysis. Figure 8.1 shows distribution plots for response entropy values on the 3 measures. In total, 13 participants were identified as having insufficient response entropy and were removed from further analysis. This left a final sample size of 529 for the main analyses.

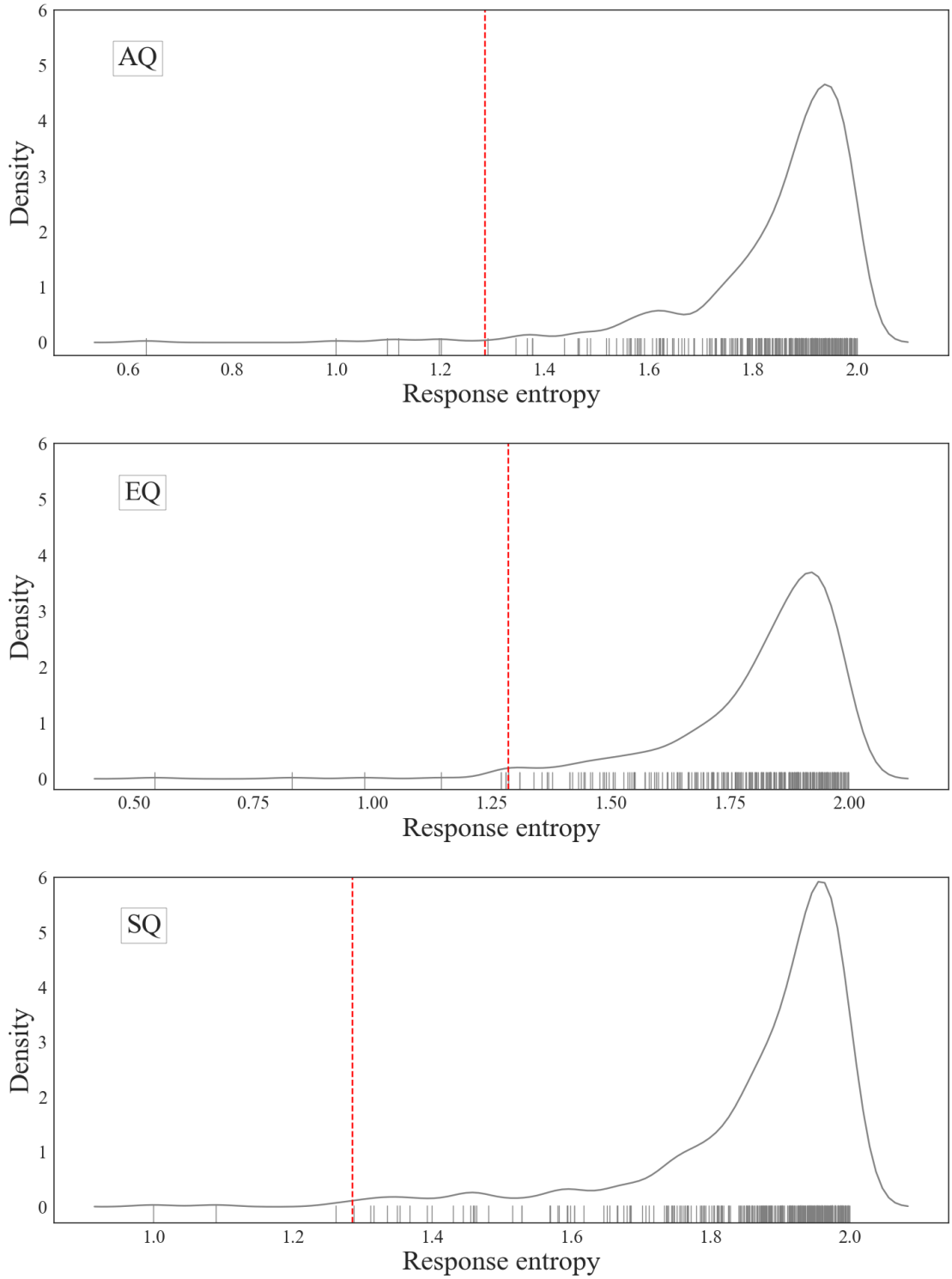


Fig. 8.1 Distributions of response entropy for the Autism Spectrum Quotient (AQ), Empathy Quotient (EQ) and Systemising Quotient-Revised (SQ). Individual data points are shown along the x-axis and the overall sample density is shown as a kernel density estimate. Cut off values are shown by the red dashed lines.

8.3.2 Age differences between the autism and control groups

The overall mean age of participants was 37.1 years old (*SD* = 12.7, range = 18 - 74). The sample was then split into two groups based on diagnostic status. Participants in the autism group were older on average (*M* = 39.0, *SD* = 12.0) and had a smaller range (18 - 66) than the control group (*M* = 34.5, *SD* = 13.1, range = 18 - 74). The age distributions in the two groups had equal variance (Levene's $F = 0.81$, $p = 0.37$) but a t-test revealed a significant difference of age between the two groups $t(527) = -4.13$, $p < 0.001$. Distributions of ages are shown in figure 8.2

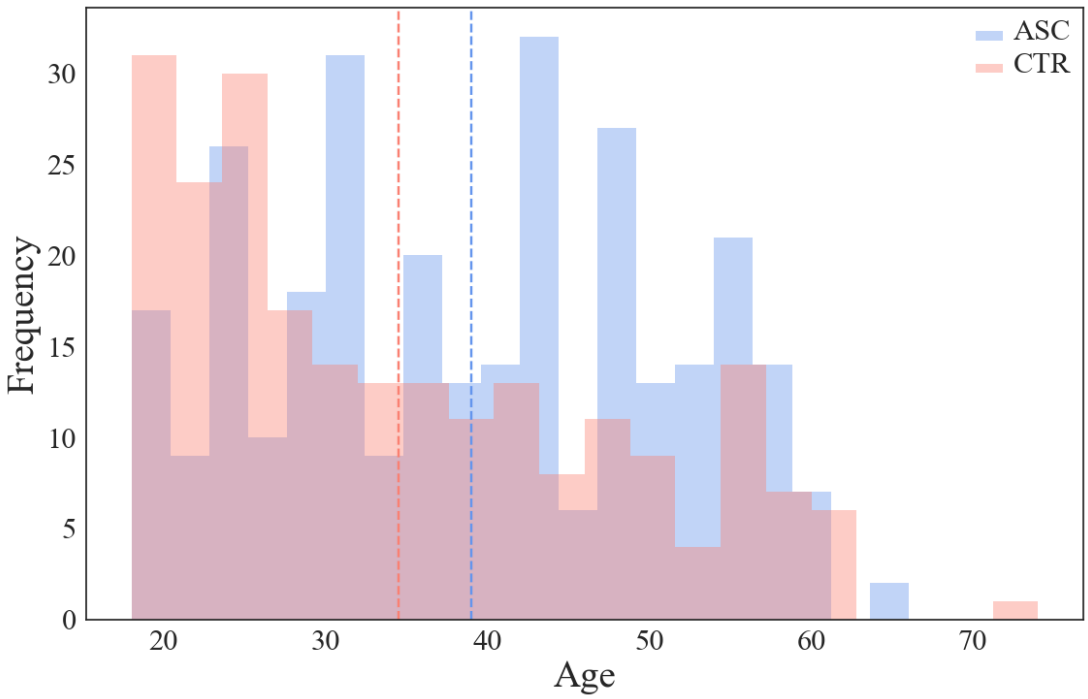


Fig. 8.2 Frequency distributions of participant ages for control (CTR) and autism (ASC) groups. Means for both groups are shown as dashed lines.

As the two groups differed significantly in terms of age, further analyses were conducted to assess whether age had a significant effect on any of the questionnaire measures. These are reported within the main descriptive analyses section.

8.3.3 Sex effects

An analysis was carried out to determine whether the sexes of participants in the two diagnostic groups were equal. A Chi-squared test was conducted on the frequencies of males

and females across the two groups ($\tilde{\chi}^2(1) = 13.5, p < 0.001$). This suggested that the ratio of male and female participants was unbalanced across the control and autism groups. This imbalance between males and females across the two groups could affect results if sex is found to have a significant effect on any of the measures. The effect of sex will be tested across all the questionnaire measures in the main descriptive analyses section. This will be considered in more detail at the end of the chapter.

8.3.4 Autism Spectrum Quotient

Distribution of responses

The AQ consists of 50 items each of which can be scored as either 0 or 1, giving a maximum possible score of 50 (Baron-Cohen et al., 2001). In total, 397 participants completed the AQ. The average score across all participants was 30.97 (*SD* = 12.05).

Sex	Diagnosis	Mean	*SD*	*N*
Male	Control	25.53	8.606	32
	Autism	36.51	11.084	92
Female	Control	23.21	9.753	128
	Autism	35.52	11.071	145

Table 8.1 Participant descriptives for the Autism Spectrum Quotient (AQ) within the full sample. Mean, standard deviation (*SD*) and sample size (*N*) are shown for all subgroups after stratifying based on sex and diagnosis.

Of the 397 participants that completed the questionnaire, 160 did not have a diagnosis of an autism spectrum condition (32 males and 128 females) and 237 reported a diagnosis (92 males and 145 females). Participant descriptives are summarised in table 8.1. The distribution of scores for all participants is shown in figure 8.3. The dotted line shows the kernel density estimate of a normal Gaussian distribution (skew and kurtosis = 0) for the mean and variance calculated for the sample.

A Kolmogorov-Smirnov (K-S) test for normality was found to be nominally significant and remained significant after applying a Bonferroni correction to account for multiple testing across the 8 different questionnaire measures ($D = 0.12$, $p < 0.001$). However, as the K-S test is particular sensitive to larger sample sizes (Ghasemi and Zahediasl, 2012), the values for the skew and kurtosis of the distribution were evaluated to decide whether the sample was suitable for parametric testing.

The skew (-0.56) and kurtosis values (-0.79) for the distribution of scores were not considered problematic as both were less than the suggested threshold values for a departure

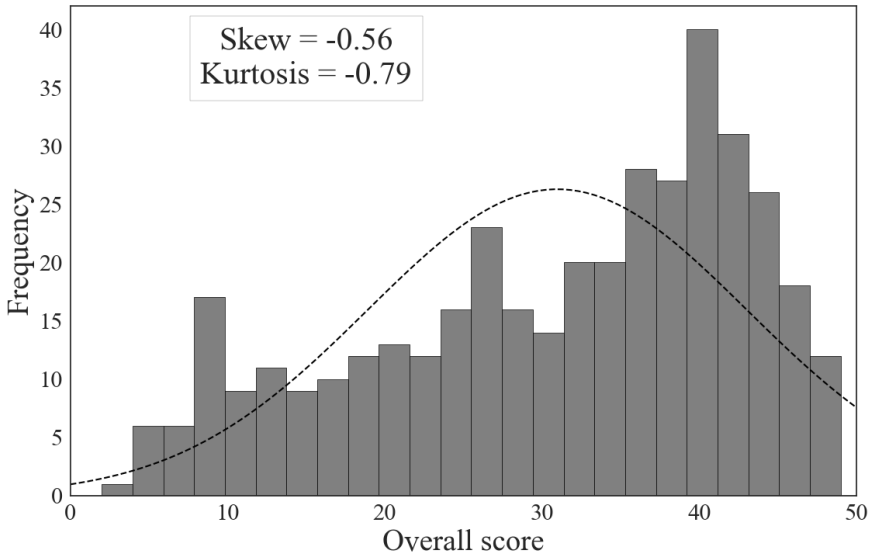


Fig. 8.3 Frequency distribution of scores on the Autism Spectrum Quotient (AQ) across all participants. The dotted line shows a kernel density estimate of a normal Gaussian distribution (skew and kurtosis = 0) based on the mean and variance of the sample.

from normality (Gravetter and Wallnau, 2010; Trochim and Donnelly, 2001). Therefore, standard parametric tests were used to evaluate potential effects of group, sex and age.

Age effects

Participants' scores were plotted against their age at time of the study for all individuals as shown in figure 8.4. A Pearson's test found a small yet nominally significant correlation between scores on the AQ and participants' ages ($r = 0.12$, $p = 0.01$). However, this fell short of significance after applying a Bonferroni correction to account for the multiple outcome measures that are being assessed.

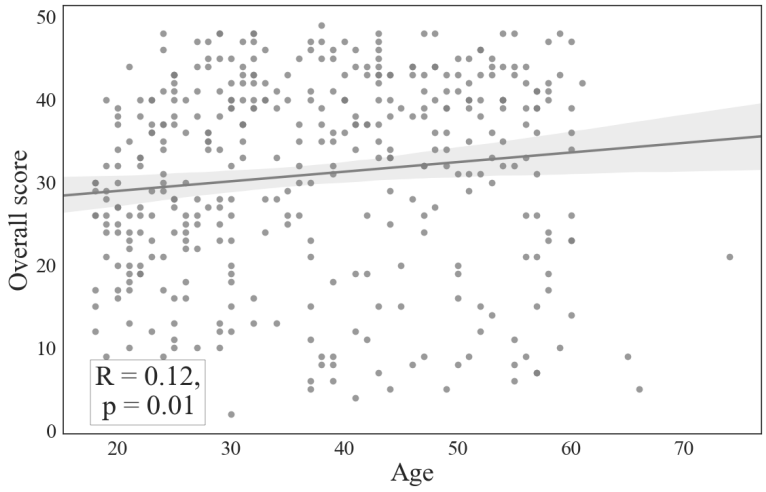


Fig. 8.4 Overall score on the Autism Spectrum Quotient (AQ) plotted against participants age.

Diagnosis and sex effects

A 2-way ANOVA was conducted with AQ as the outcome measure and diagnostic status and sex as the 2 independent variables. Type III Sum of Squares was used to reduce any potential influence from the imbalance of males and females between the autism and control groups. There was a significant effect of diagnostic status which remained significant after correcting for multiple testing ($F(1, 393) = 86.79$, $p < 0.001$, $\eta^2 = 0.18$).

Cases	Sum of Squares	*df*	Mean Square	*F*	*p*	η^2
Sex	193.25	1	193.25	1.758	0.186	0.004
Diagnosis	9541.57	1	9541.57	86.793	< .001	0.180
Sex * Diagnosis	30.97	1	30.97	0.282	0.596	0.001
Residual	43204.47	393	109.94			

Table 8.2 Results from the 2-way ANOVA run on the full sample. Scores on the Autism Spectrum Quotient (AQ) were used as the outcome measure and diagnostic status and sex were used as the 2 independent variables.

There was neither a significant effect of sex ($F(1, 393) = 1.76$, $p = 0.186$, $\eta^2 = 0.004$) nor a significant interaction between diagnostic status and sex ($F(1, 393) = 0.60$, $p > 0.3$, $\eta^2 = 0.001$, see table 8.2). An additional Bayesian analysis of variance was carried out using the JASP software package (JASP Team, 2016) to establish whether there was support for the absence of an effect of sex (evidence in favor of the null), rather than just insufficient evidence

to support the existence of a true effect. The inclusion Bayes Factor for a particular variable shows the relative evidence for a difference between the model with and without that variable included. There was very strong evidence to suggest that diagnostic group had a significant effect on AQ ($BF_{inclusion} > 1000$) whereas there was moderate evidence in support of a lack of both a direct effect of sex and interaction effect of sex and diagnosis ($BF_{inclusion} = 0.194$ and $BF_{inclusion} = 0.164$ respectively). Taken as a whole, the results suggested that there was no direct or interaction effect of sex in the sample. The distributions of responses for each subgroup are shown as violin plots (Hintze and Nelson, 1998) in figure 8.5.

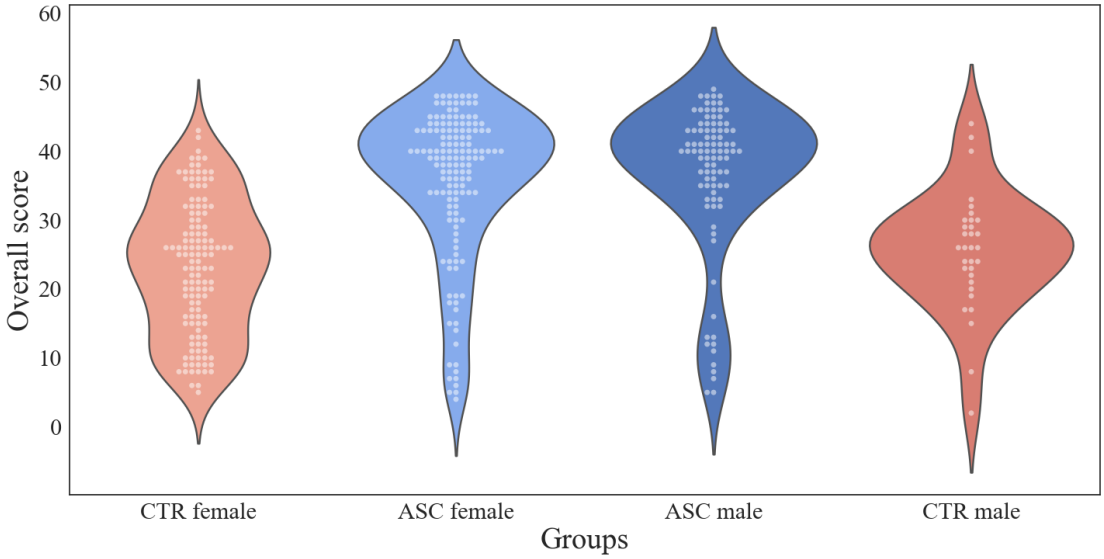


Fig. 8.5 Distributions of overall scores on the Autism Spectrum Quotient (AQ). Individual data points are overlaid on top of violin plot outlines showing the kernel probability density. Data are shown for all subgroups after stratifying based on sex and diagnosis.

8.3.5 Empathy Quotient

Distribution of responses

The EQ consists of 40 items each of which can be scored as either 0, 1 or 2, giving a maximum possible score of 80 (Baron-Cohen and Wheelwright, 2004). In total, 398 participants completed the EQ. The average score across all participants was 23.96 (SD = 16.83). Participant descriptives are summarised in full in table 8.3. Again, there was a low number of male participants without a diagnosis relative to other groups. This imbalance was a recurring

issue across all questionnaire measures and so will be mentioned again until the summary at the end of the chapter.

Sex	Diagnosis	Mean	*SD*	*N*
Male	Control	26.30	18.83	33
	ACS	18.65	13.42	91
Female	Control	29.05	21.34	132
	Autism	22.08	11.55	142

Table 8.3 Participant descriptives for the Empathy Quotient (EQ) within the full sample. Mean, standard deviation (*SD*) and sample size (*N*) are shown for all subgroups after stratifying based on sex and diagnosis.

The distribution of scores for all participants is shown in figure 8.6. The dotted line shows the kernel density estimate of a normal Gaussian distribution (skew and kurtosis = 0) for the mean and variance calculated for the sample.

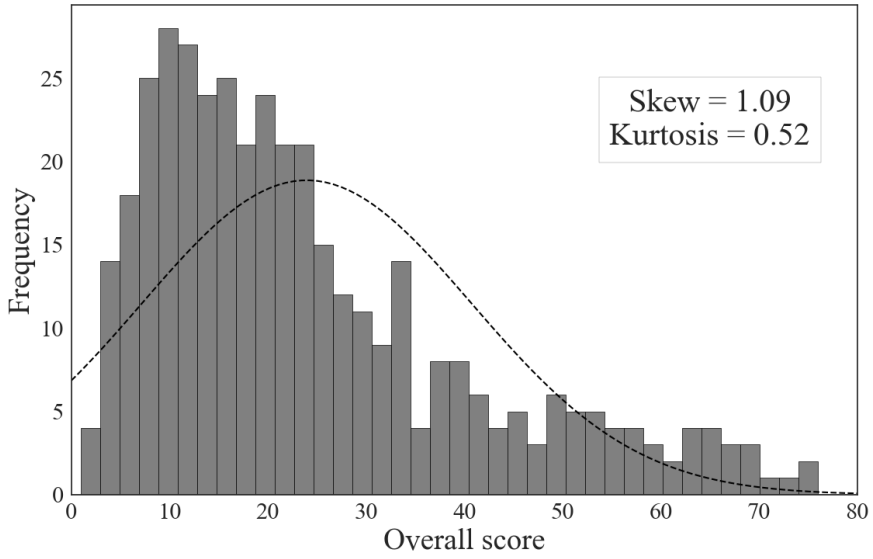


Fig. 8.6 Frequency distribution of scores on the Empathy Quotient (EQ) across all participants. The dotted line shows a kernel density estimate of a normal Gaussian distribution (skew and kurtosis = 0) based on the mean and variance of the sample.

The Kolmogorov-Smirnov (K-S) test for normality was found to be nominally significant and remained significant after applying a Bonferroni correction to account for multiple testing across the 8 different questionnaire measures ($D = 0.13$, $p < 0.001$). Again, due to

oversensitivity of the K-S test in large samples, the values for the skew and kurtosis of the distribution were evaluated.

The skew (1.09) and kurtosis values (0.52) for the distribution of scores were not considered problematic. The slight positive skew could possibly be driven by the fact that the sample has a greater number of autistic individuals than non-autistic individuals and the fact that autistic individuals are expected to obtain lower scores on the EQ (Baron-Cohen and Wheelwright, 2004). As both skew and kurtosis values were satisfactory for the assumption of normality, standard parametric tests were used to evaluate potential effects of group, sex and age.

Age effects

Participants' scores were plotted against their age at time of the study for all individuals as shown in figure 8.7. A Pearson's test found that the correlation between scores on the EQ and participants' ages failed to reach nominal significance ($r = 0.09$, $p = 0.06$).

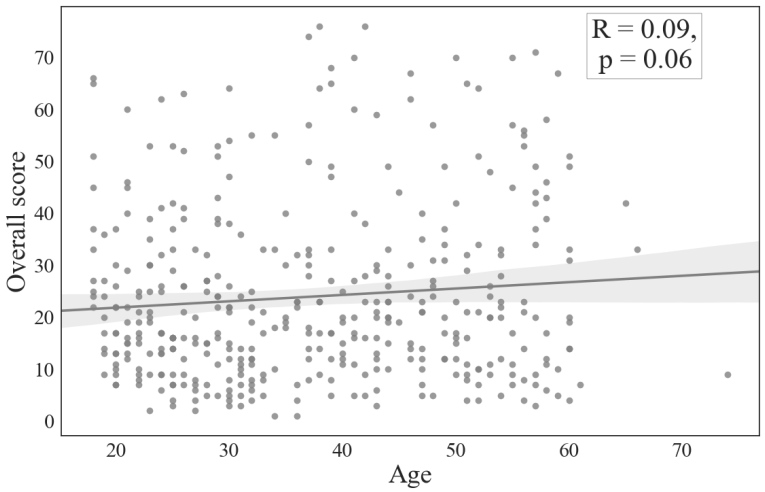


Fig. 8.7 Overall score on the Empathy Quotient (EQ) plotted against participants age.

Diagnosis and sex effects

A 2-way ANOVA was conducted with EQ as the outcome measure and diagnostic status and sex as the 2 independent variables. Type III Sum of Squares was used to reduce any potential influence from the imbalance of males and females between the autism and control groups.

There was a significant effect of diagnostic status which remained significant after correcting for multiple testing ($F(1, 394) = 14.2$, $p < 0.001$, $\eta^2 = 0.035$).

Cases	Sum of Squares	*df*	Mean Square	*F*	*p*	η^2
Sex	682.790	1	682.790	2.538	0.112	0.006
Diagnosis	3820.718	1	3820.718	14.200	< .001	0.035
Sex * Diagnosis	8.608	1	8.608	0.032	0.858	0.000
Residual	106014.430	394	269.072			

Table 8.4 Results from the 2-way ANOVA run on the full sample. Scores on the Empathy Quotient (EQ) were used as the outcome measure and diagnostic status and sex were used as the 2 independent variables.

There was neither a significant effect of sex ($F(1, 394) = 2.54$, $p = 0.112$, $\eta^2 = 0.006$) or significant interaction between diagnostic status and sex ($F(1, 394) = 0.032$, $p > 0.3$, $\eta^2 = 0.000$, see table 8.2). There was very strong evidence to suggest that diagnostic group had a significant effect on EQ ($BF_{inclusion} = 773.04$) whereas there was weak evidence in support of a lack of a direct effect of sex and modest evidence in support of a lack of interaction effect between sex and diagnosis ($BF_{inclusion} = 0.451$ and $BF_{inclusion} = 0.245$ respectively). Taken as a whole, I believe the results suggest that there is no direct or interaction effect of sex in the sample (see figure 8.8).

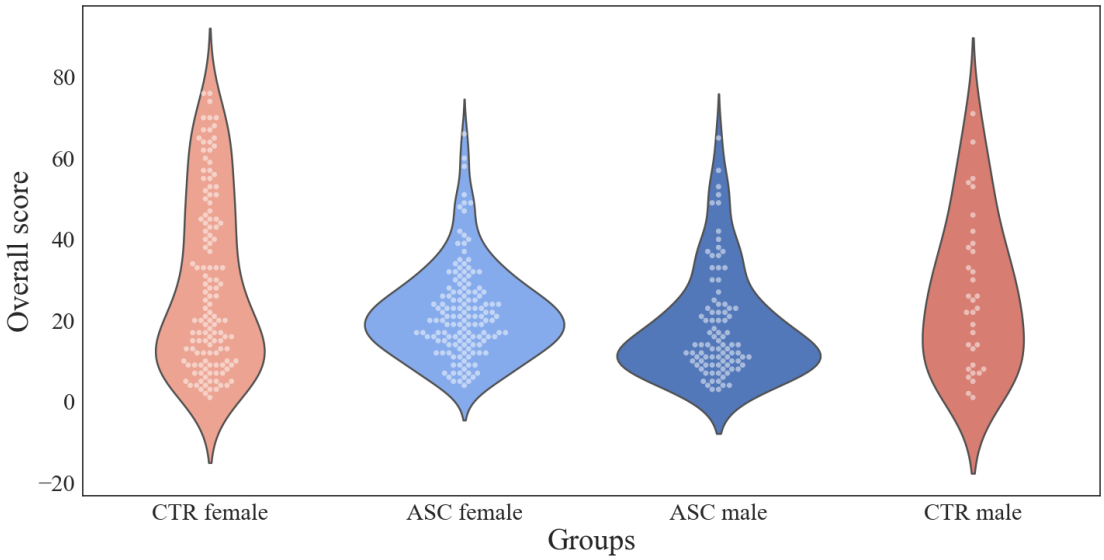


Fig. 8.8 Distributions of overall scores on the Empathy Quotient (EQ). Individual data points are overlaid on top of violin plot outlines showing the kernel probability density. Data are shown for all subgroups after stratifying based on sex and diagnosis.

8.3.6 Systemising Quotient-Revised

Distribution of responses

The SQ consists of 75 items each of which can be scored as either 0, 1 or 2, giving a maximum possible score of 150 (Baron-Cohen et al., 2003). A total of 386 participants completed the SQ. The average score across all participants was 65.89 (*SD* = 24.9). Participant descriptives are summarised in full in table 8.5.

Sex	Diagnosis	Mean	*SD*	*N*
Male	Control	54.39	22.54	33
	Autism	73.60	29.07	88
Female	Control	56.71	19.66	126
	Autism	72.06	23.43	139

Table 8.5 Participant descriptives for the Systemising Quotient-Revised (SQ) within the full sample. Mean, standard deviation (*SD*) and sample size (*N*) are shown for all subgroups after stratifying based on sex and diagnosis.

The distribution of scores for all participants is shown in figure 8.9. The K-S test for normality was non-significant ($D = 0.033$, $p > 0.3$) and the skew (0.05) and kurtosis values (-0.5) for the distribution of scores also suggested that the assumption of normality held.

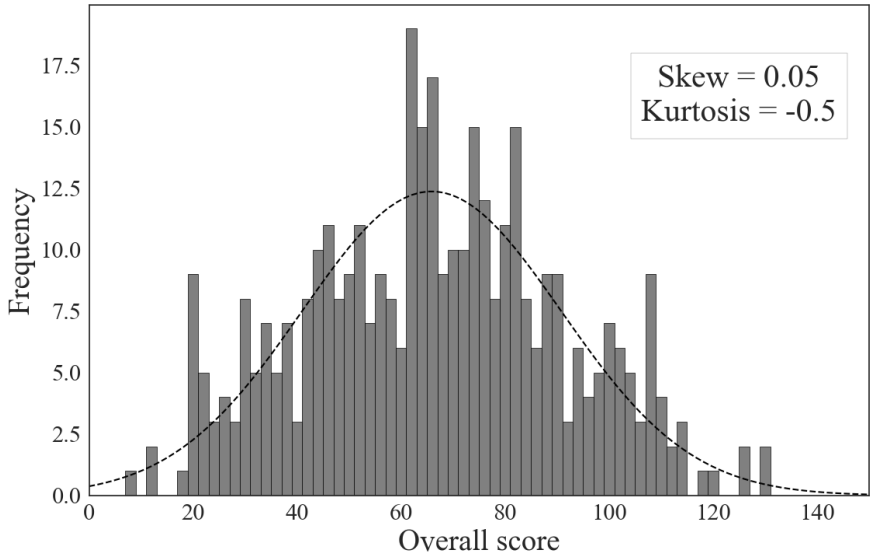


Fig. 8.9 Frequency distribution of scores on the Systemising Quotient-Revised (SQ) across all participants. The dotted line shows a kernel density estimate of a normal Gaussian distribution (skew and kurtosis = 0) based on the mean and variance of the sample.

Age effects

Participants' scores were plotted against their age at time of the study for all individuals as shown in figure 8.10. The Pearson's test found that the correlation between scores on the SQ and participants' ages just reached nominal significance ($r = 0.1$, $p = 0.05$) but this did not remain significant after applying a Bonferroni correction.

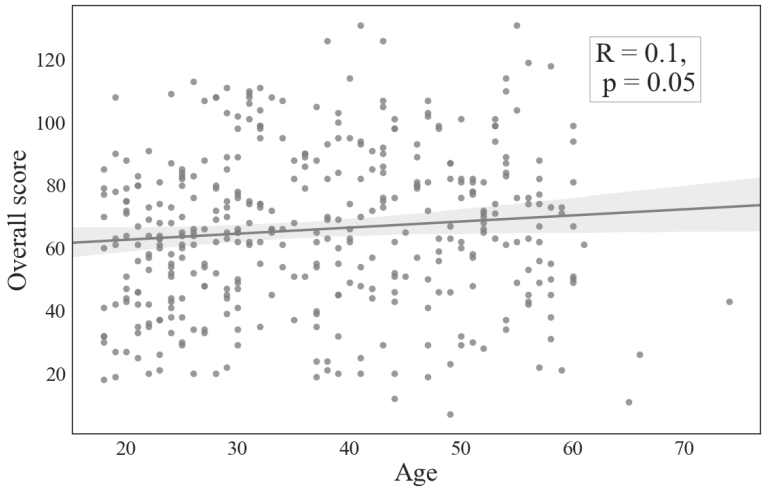


Fig. 8.10 Overall score on the Systemising Quotient-Revised (SQ) plotted against participants age.

Diagnosis and sex effects

A 2-way ANOVA was conducted with SQ as the outcome measure and diagnostic status and sex as the 2 independent variables. Type III Sum of Squares was used to reduce any potential influence from the imbalance of males and females between the autism and control groups. There was a significant effect of diagnostic status which remained significant after correcting for multiple testing ($F(1, 382) = 37.55$, $p < 0.001$, $\eta^2 = 0.089$).

Cases	Sum of Squares	*df*	Mean Square	*F*	*p*	η^2
Sex	10.59	1	10.59	0.019	0.891	0.000
Diagnosis	21018.79	1	21018.79	37.548	< .001	0.089
Sex * Diagnosis	263.02	1	263.02	0.470	0.493	0.001
Residual	213838.21	382	559.79			

Table 8.6 Results from the 2-way ANOVA run on the full sample. Scores on the Systemising Quotient-Revised (SQ) were used as the outcome measure and diagnostic status and sex were used as the 2 independent variables.

There was neither a significant effect of sex ($F(1, 382) = 0.019$, $p > 0.3$, $\eta^2 = 0.000$) or significant interaction between diagnostic status and sex ($F(1, 382) = 0.47$, $p > 0.3$, $\eta^2 = 0.001$, see table 8.6). There was very strong evidence to suggest that diagnostic group had a significant effect on SQ ($BF_{inclusion} > 1000$) and there was modest to strong evidence in support of a lack of a direct effect of sex and interaction effect between sex and diagnosis

($BF_{inclusion} = 0.095$ and $BF_{inclusion} = 0.092$ respectively). The results suggest that there is no direct or interaction effect of sex in the sample (see figure 8.11).

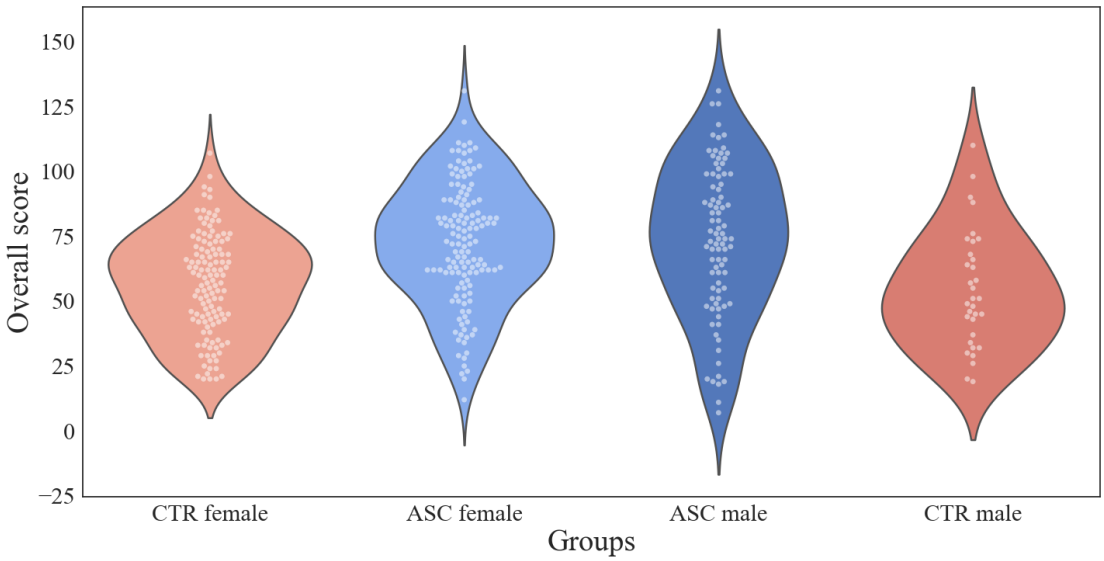


Fig. 8.11 Distributions of overall scores on the Systemising Quotient-Revised (SQ). Individual data points are overlaid on top of violin plot outlines showing the kernel probability density. Data are shown for all subgroups after stratifying based on sex and diagnosis.

8.3.7 Glasgow Sensory Questionnaire

Distribution of responses

The GSQ consists of 41 items each of which can be scored from 0 to 4, giving a maximum possible score of 168 (Robertson and Simmons, 2013). A total of 451 participants completed the GSQ. The average score across all participants was 63.16 (SD = 27.03). Participant descriptives are summarised in full in table 8.7.

The distribution of scores for all participants is shown in figure 8.12. The K-S test for normality was non-significant (D = 0.039, $p > 0.3$) and the skew (0.25) and kurtosis values (-0.38) for the distribution of scores also suggested that the assumption of normality held.

Sex	Diagnosis	Mean	*SD*	*N*
Male	Control	44.02	23.35	40
	Autism	73.02	25.00	103
Female	Control	45.96	20.51	144
	Autism	76.74	23.09	164

Table 8.7 Participant descriptives for the Glasgow Sensory Questionnaire (GSQ) within the full sample. Mean, standard deviation (*SD*) and sample size (*N*) are shown for all subgroups after stratifying based on sex and diagnosis.

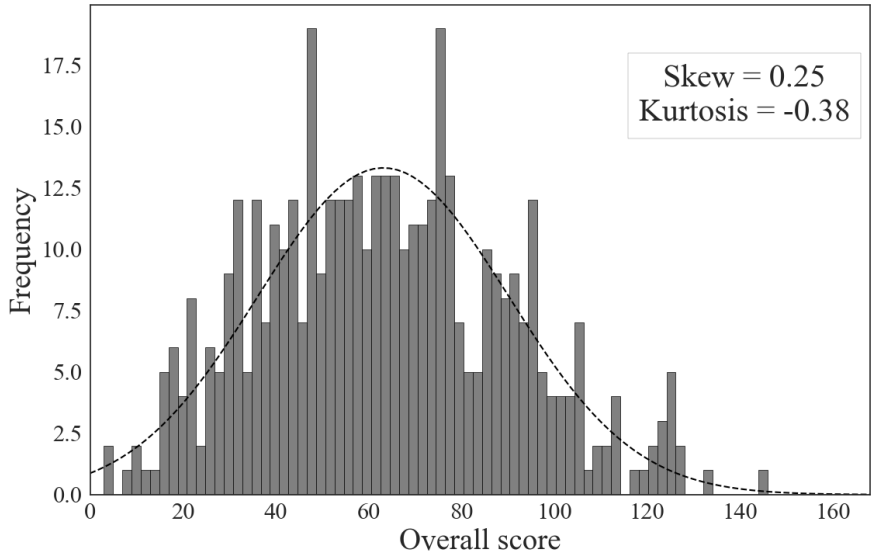


Fig. 8.12 Frequency distribution of scores on the Glasgow Sensory Questionnaire (GSQ) across all participants. The dotted line shows a kernel density estimate of a normal Gaussian distribution (skew and kurtosis = 0) based on the mean and variance of the sample.

Age effects

Participants' scores were plotted against their age at time of the study for all individuals as shown in figure 8.13. The Pearson's test found that the correlation between scores on the GSQ and participants' ages failed to reach nominal significance (r = -0.02, $p > 0.3$).

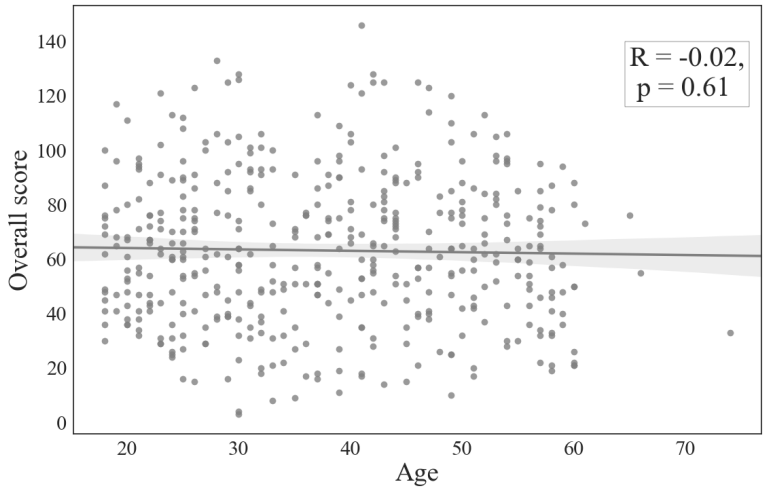


Fig. 8.13 Overall score on the Glasgow Sensory Questionnaire (GSQ) plotted against participants age.

Diagnosis and sex effects

A 2-way ANOVA was conducted with GSQ as the outcome measure and diagnostic status and sex as the 2 independent variables. Type III Sum of Squares was used to reduce any potential influence from the imbalance of males and females between the autism and control groups. There was a significant effect of diagnostic status which remained significant after correcting for multiple testing ($F(1, 447) = 144.13$, $p < 0.001$, $\eta^2 = 0.243$).

Cases	Sum of Squares	*df*	Mean Square	*F*	*p*	η^2
Sex	668.93	1	668.93	1.289	0.257	0.002
Diagnosis	74824.34	1	74824.34	144.128	< .001	0.243
Sex * Diagnosis	66.73	1	66.73	0.129	0.720	0.000
Residual	232060.41	447	519.15			

Table 8.8 Results from the 2-way ANOVA run on the full sample. Scores on the Glasgow Sensory Questionnaire (GSQ) were used as the outcome measure and diagnostic status and sex were used as the 2 independent variables.

There was neither a significant effect of sex ($F(1, 382) = 1.289$, $p = 0.26$, $\eta^2 = 0.002$) or significant interaction between diagnostic status and sex ($F(1, 382) = 0.129$, $p > 0.3$, $\eta^2 = 0.000$, see table 8.8). There was very strong evidence to suggest that diagnostic group had a significant effect on GSQ ($BF_{inclusion} > 1000$) and there was modest evidence in support of a lack of a direct effect of sex and interaction effect between sex and diagnosis

($BF_{inclusion} = 0.20$ and $BF_{inclusion} = 0.15$ respectively). The results suggest that there is no direct or interaction effect of sex in the sample (see figure 8.14).

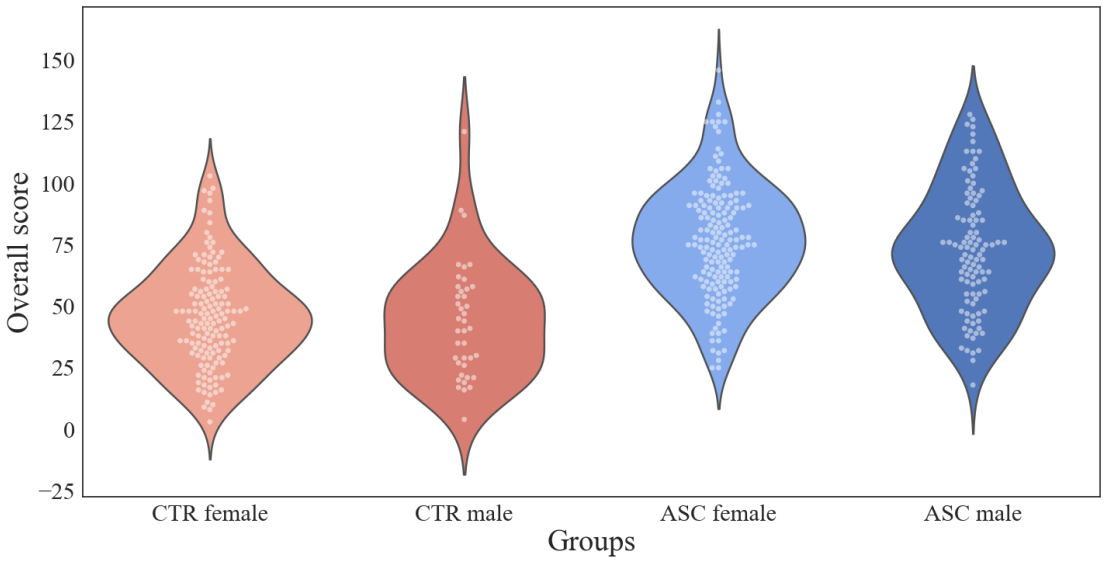


Fig. 8.14 Distributions of overall scores on the Glasgow Sensory Questionnaire (GSQ). Individual data points are overlaid on top of violin plot outlines showing the kernel probability density. Data are shown for all subgroups after stratifying based on sex and diagnosis.

8.3.8 Zung Self-rating Anxiety Scale

Distribution of responses

The ZAS consists of 20 items each of which can be scored from 1 to 4, giving a maximum possible score of 80 (Zung, 1971). A total of 454 participants completed the ZAS. The average score across all participants was 40.36 (SD = 10.44). Participant descriptives are summarised in full in table 8.9.

The distribution of scores for all participants is shown in figure 8.15. The K-S test for normality was nominally significant (D = 0.077, p = 0.007) but did not reach significance after applying the Bonferroni correction. The skew (0.6) and kurtosis values (0.0) for the distribution of scores where within the acceptable range and so it appears the assumption of normality held.

Sex	Diagnosis	Mean	*SD*	*N*
Male	Control	34.10	9.016	41
	Autism	41.21	11.361	102
Female	Control	37.42	9.633	146
	Autism	44.00	9.451	165

Table 8.9 Participant descriptives for the Zung Self-rating Anxiety Scale (ZAS) within the full sample. Mean, standard deviation (*SD*) and sample size (*N*) are shown for all subgroups after stratifying based on sex and diagnosis.

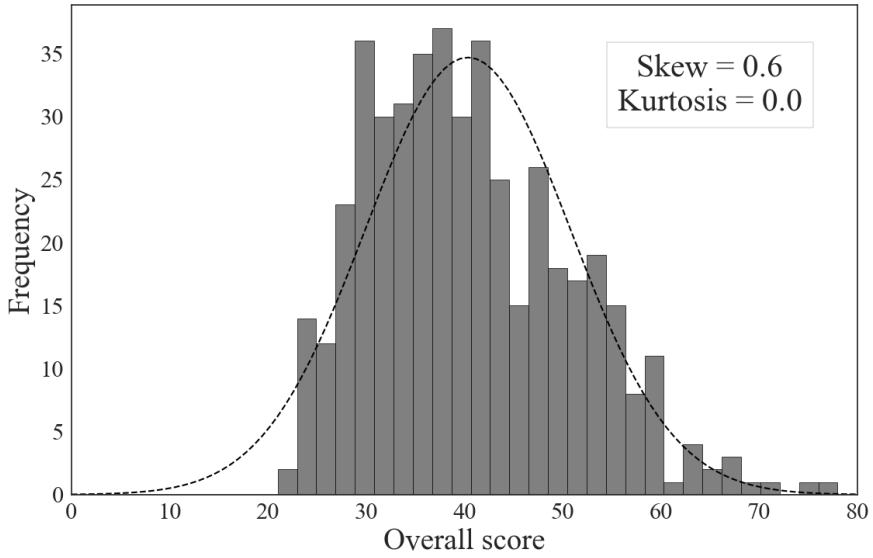


Fig. 8.15 Frequency distribution of scores on the Zung Self-rating Anxiety Scale (ZAS) across all participants. The dotted line shows a kernel density estimate of a normal Gaussian distribution (skew and kurtosis = 0) based on the mean and variance of the sample.

Age effects

Participants' scores were plotted against their age at time of the study for all individuals as shown in figure 8.16. The Pearson's test found that the correlation between scores on the ZAS and participants' ages failed to reach nominal significance (r = -0.06, p = 0.21).

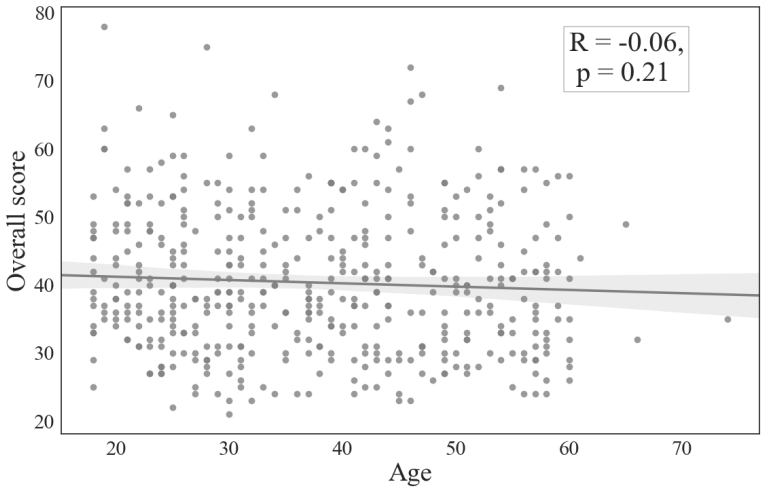


Fig. 8.16 Overall score on the Zung Self-rating Anxiety Scale (ZAS) plotted against participants age.

Diagnosis and sex effects

A 2-way ANOVA was conducted with ZAS as the outcome measure and diagnostic status and sex as the 2 independent variables. Type III Sum of Squares was used to reduce any potential influence from the imbalance of males and females between the autism and control groups. There was a significant effect of diagnostic status which remained significant after correcting for multiple testing ($F(1, 450) = 40.34$, $p < 0.001$, $\eta^2 = 0.081$).

Cases	Sum of Squares	*df*	Mean Square	*F*	*p*	η^2
Sex	793.678	1	793.678	8.046	0.005	0.016
Diagnosis	3979.063	1	3979.063	40.336	< .001	0.081
Sex * Diagnosis	5.877	1	5.877	0.060	0.807	0.000
Residual	44391.800	450	98.648			

Table 8.10 Results from the 2-way ANOVA run on the full sample. Scores on the Zung Self-rating Anxiety Scale (ZAS) were used as the outcome measure and diagnostic status and sex were used as the 2 independent variables.

There a significant effect of sex ($F(1, 450) = 8.05$, $p = 0.26$, $\eta^2 = 0.016$) which remained significant after applying the Bonferroni correction. The interaction effect between diagnostic status and sex did not reach significance ($F(1, 450) = 0.06$, $p > 0.3$, $\eta^2 = 0.000$, see table 8.10). There was very strong evidence to suggest that diagnostic group had a significant effect on ZAS scores ($BF_{inclusion} > 1000$) and there was moderate evidence in support of an

effect of sex ($BF_{inclusion} = 4.9$). There was weak evidence to support a lack of interaction effect between sex and diagnosis ($BF_{inclusion} = 0.59$). The results suggest that there is a direct effect of sex on ZAS scores in the sample (see figure 8.17).

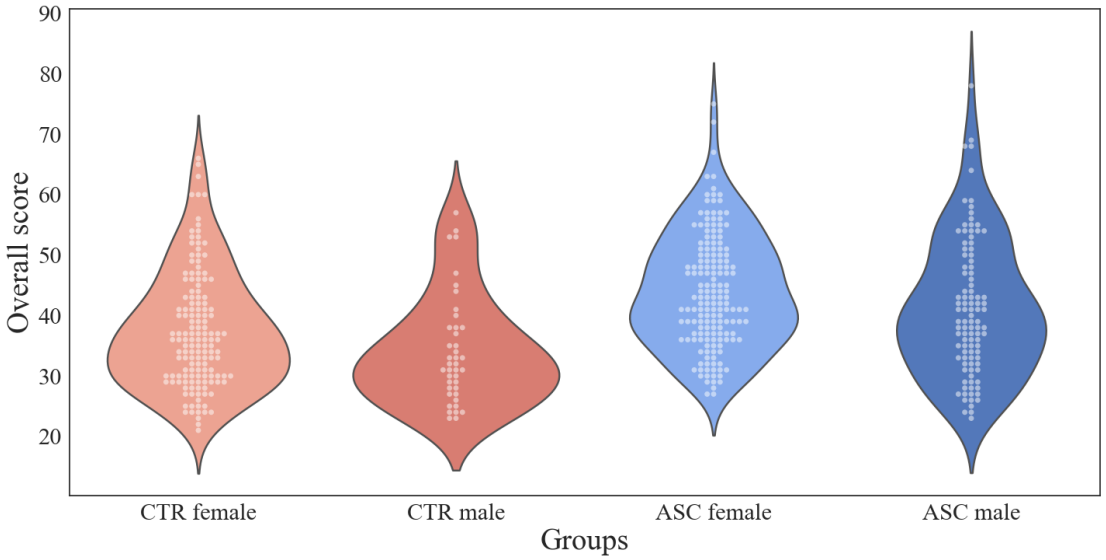


Fig. 8.17 Distributions of overall scores on the Zung Self-rating Anxiety Scale (ZAS). Individual data points are overlaid on top of violin plot outlines showing the kernel probability density. Data are shown for all subgroups after stratifying based on sex and diagnosis.

8.3.9 Toronto Alexithymia Scale-II

Distribution of responses

The twenty-item TAS consists of 20 items each of which can be scored from 1 to 5, giving a maximum possible score of 100 (Bagby et al., 1994). A total of 448 participants completed the TAS. The average score across all participants was 56.73 (SD = 14.94). Participant descriptives are summarised in full in table 8.11.

The distribution of scores for all participants is shown in figure 8.18. The K-S test for normality was nominally significant (D = 0.071, p = 0.021) but did not reach significance after applying the Bonferroni correction. The skew (-0.14) and kurtosis values (-0.86) for the distribution of scores where within the acceptable range.

Sex	Diagnosis	Mean	*SD*	*N*
Male	Control	47.17	11.87	41
	Autism	62.71	13.20	103
Female	Control	47.55	13.36	142
	Autism	63.40	12.43	162

Table 8.11 Participant descriptives for the Toronto Alexithymia Scale-II (TAS) within the full sample. Mean, standard deviation (*SD*) and sample size (*N*) are shown for all subgroups after stratifying based on sex and diagnosis.

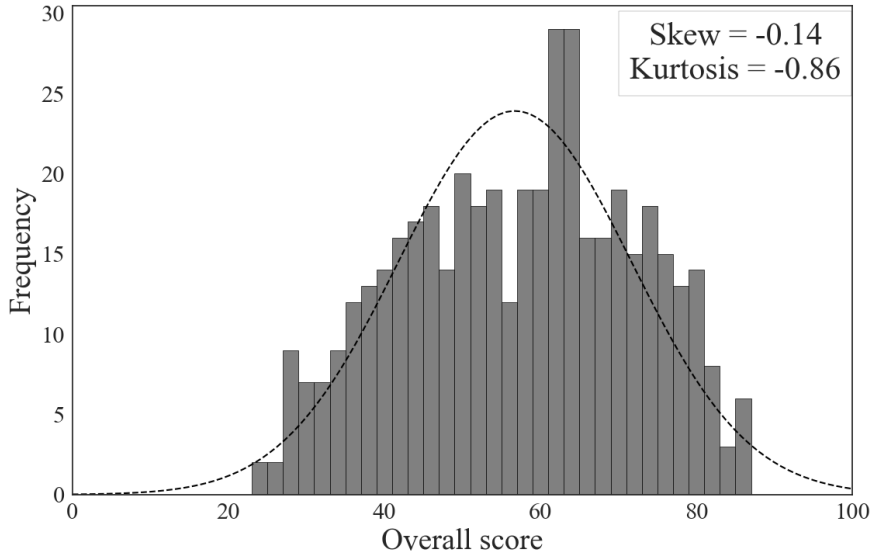


Fig. 8.18 Frequency distribution of scores on the Toronto Alexithymia Scale-II (TAS) across all participants. The dotted line shows a kernel density estimate of a normal Gaussian distribution (skew and kurtosis = 0) based on the mean and variance of the sample.

Age effects

Participants' scores were plotted against their age at time of the study for all individuals as shown in figure 8.19. The Pearson's test found that the correlation between scores on the TAS and participants' failed to reach nominal significance ($r = 0.08$, $p = 0.1$).

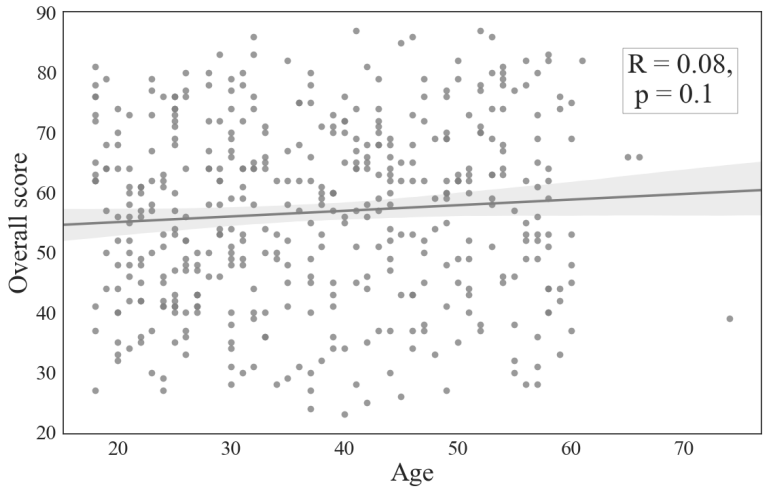


Fig. 8.19 Overall score on the Toronto Alexithymia Scale-II (TAS) plotted against participants age.

Diagnosis and sex effects

A 2-way ANOVA was conducted with scores on the TAS as the outcome measure and diagnostic status and sex as the 2 independent variables. Type III Sum of Squares was used to reduce any potential influence from the imbalance of males and females between the autism and control groups. There was a significant effect of diagnostic status which remained significant after correcting for multiple testing ($F(1, 444) = 125.90$, $p < 0.001$, $\eta^2 = 0.221$).

Cases	Sum of Squares	*df*	Mean Square	*F*	*p*	η^2
Sex	24.246	1	24.246	0.147	0.702	0.000
Diagnosis	20825.276	1	20825.276	125.896	$< .001$	0.221
Sex * Diagnosis	2.083	1	2.083	0.013	0.911	0.000
Residual	73445.142	444	165.417			

Table 8.12 Results from the 2-way ANOVA run on the full sample. Scores on the Toronto Alexithymia Scale-II (TAS) were used as the outcome measure and diagnostic status and sex were used as the 2 independent variables.

There was neither a significant effect of sex ($F(1, 444) = 0.147$ $p > 0.3$, $\eta^2 = 0.000$) or significant interaction between diagnostic status and sex ($F(1, 444) = 0.013$, $p > 0.3$, $\eta^2 = 0.000$, see table 8.12). There was very strong evidence to suggest that diagnostic group had a significant effect on TAS scores ($BF_{inclusion} > 1000$) and there was modest-strong evidence in support of a lack of a direct effect of sex and interaction effect between sex and diagnosis

($BF_{inclusion} = 0.096$ and $BF_{inclusion} = 0.073$ respectively). The results suggest that there is no direct or interaction effect of sex in the sample (see figure 8.20).

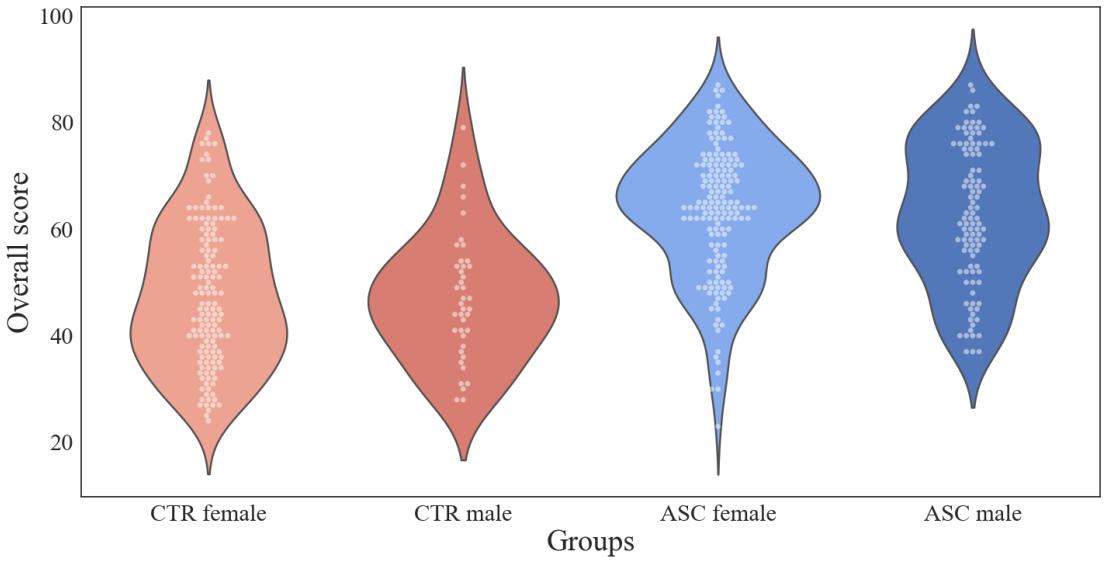


Fig. 8.20 Distributions of overall scores on the Toronto Alexithymia Scale-II (TAS). Individual data points are overlaid on top of violin plot outlines showing the kernel probability density. Data are shown for all subgroups after stratifying based on sex and diagnosis.

8.3.10 The Obsessive-Compulsive Inventory-Revised

Distribution of responses

The OCI consists of 18 items each of which can be scored from 0 to 4, giving a maximum possible score of 72 (Foa et al., 2002). A total of 450 participants completed the OCI. The average score across all participants was 20.57 (SD = 14.11). Participant descriptives are summarised in full in table 8.13.

The distribution of scores for all participants is shown in figure 8.21. The K-S test for normality was nominally significant (D = 0.1, $p < 0.001$) and remained significant after applying the Bonferroni correction. However, the skew (0.84) and kurtosis values (0.28) for the distribution of scores where within the acceptable range suggesting that the assumption of normality was held.

Sex	Diagnosis	Mean	*SD*	*N*
Male	Control	12.47	10.74	43
	Autism	26.10	14.30	104
Female	Control	13.54	10.54	142
	Autism	25.37	13.98	161

Table 8.13 Participant descriptives for the Obsessive-Compulsive Inventory-Revised (OCI) within the full sample. Mean, standard deviation (*SD*) and sample size (*N*) are shown for all subgroups after stratifying based on sex and diagnosis.

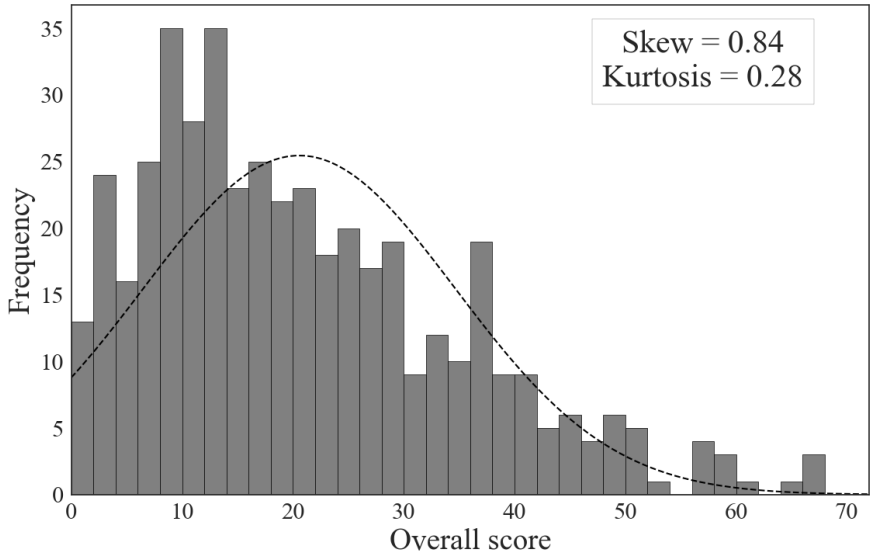


Fig. 8.21 Frequency distribution of scores on the Obsessive-Compulsive Inventory-Revised (OCI) across all participants. The dotted line shows a kernel density estimate of a normal Gaussian distribution (skew and kurtosis = 0) based on the mean and variance of the sample.

Age effects

Participants' scores were plotted against their age at time of the study for all individuals as shown in figure 8.22. The Pearson's test found that the correlation between scores on the OCI and participants' ages failed to reach nominal significance (r = -0.01, p = 0.84).

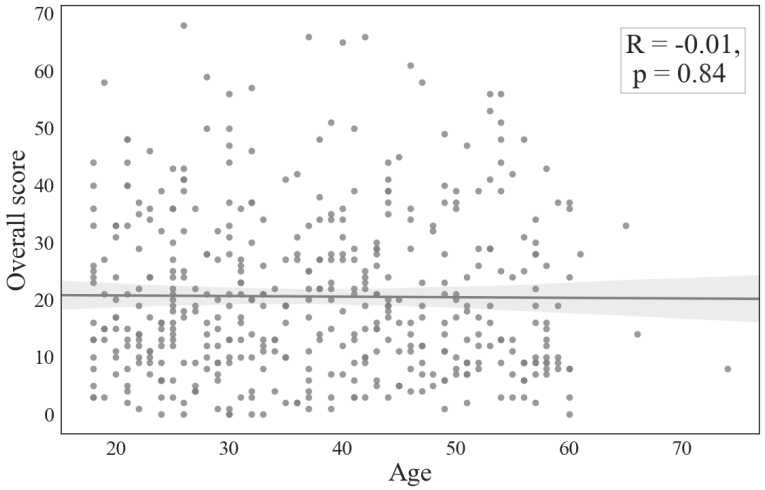


Fig. 8.22 Overall score on the Obsessive-Compulsive Inventory-Revised (OCI) plotted against participants age.

Diagnosis and sex effects

A 2-way ANOVA was conducted with scores on the OCI as the outcome measure and diagnostic status and sex as the 2 independent variables. Type III Sum of Squares was used to reduce any potential influence from the imbalance of males and females between the autism and control groups. There was a significant effect of diagnostic status which remained significant after correcting for multiple testing ($F(1, 446) = 86.14$, $p < 0.001$, $\eta^2 = 0.162$).

Cases	Sum of Squares	*df*	Mean Square	*F*	*p*	η^2
Sex	2.605	1	2.605	0.016	0.900	0.000
Diagnosis	14062.862	1	14062.862	86.139	< .001	0.162
Sex * Diagnosis	69.744	1	69.744	0.427	0.514	0.001
Residual	72812.700	446	163.257			

Table 8.14 Results from the 2-way ANOVA run on the full sample. Scores on the Obsessive-Compulsive Inventory-Revised (OCI) were used as the outcome measure and diagnostic status and sex were used as the 2 independent variables.

There was neither a significant effect of sex ($F(1, 446) = 0.016$ $p > 0.3$, $\eta^2 = 0.000$) or significant interaction between diagnostic status and sex ($F(1, 446) = 0.427$, $p > 0.3$, $\eta^2 = 0.001$, see table 8.14). There was very strong evidence to suggest that diagnostic group had a significant effect on OCI scores ($BF_{inclusion} > 1000$) and there was modest-strong evidence in support of a lack of a direct effect of sex and interaction effect between sex and diagnosis

($BF_{inclusion} = 0.087$ and $BF_{inclusion} = 0.077$ respectively). The results suggest that there is no direct or interaction effect of sex in the sample (see figure 8.23).

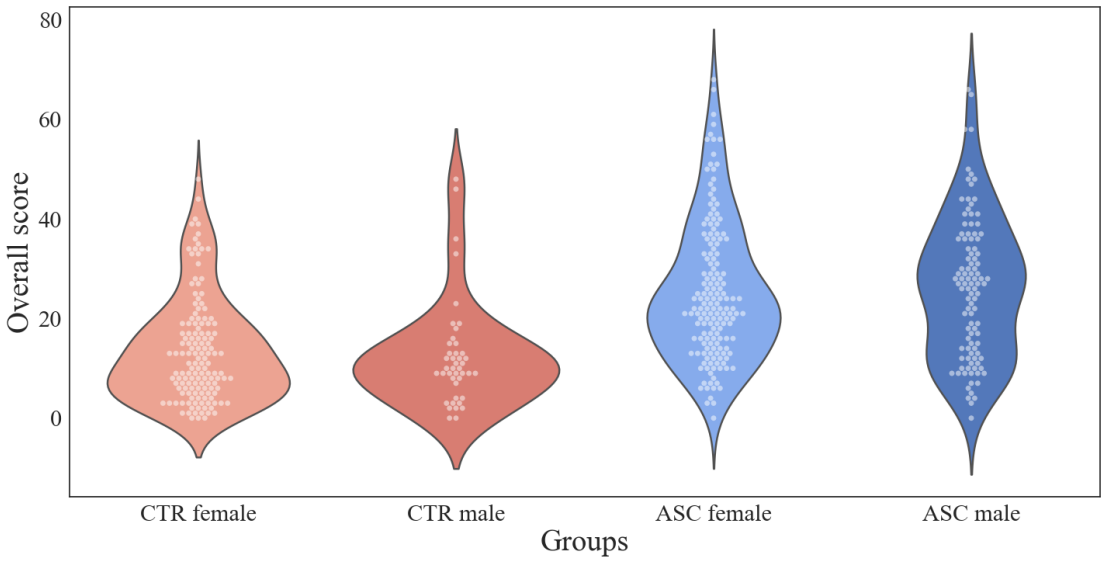


Fig. 8.23 Distributions of overall scores on the Obsessive-Compulsive Inventory-Revised (OCI). Individual data points are overlaid on top of violin plot outlines showing the kernel probability density. Data are shown for all subgroups after stratifying based on sex and diagnosis.

8.3.11 Intolerance of Uncertainty Scale

Distribution of responses

The IUS consists of 27 items each of which can be scored from 1 to 5, giving a maximum possible score of 135 (Buhr and Dugas, 2002; Freeston et al., 1994). A total of 448 participants completed the IUS. The average score across all participants was 76.81 (SD = 25.97). Participant descriptives are summarised in full in table 8.15.

The distribution of scores for all participants is shown in figure 8.24. The K-S test for normality failed to reach nominal significance (D = 0.05, p = 0.15) and the skew (0.03) and kurtosis values (-0.88) for the distribution of scores where within the acceptable range.

Sex	Diagnosis	Mean	*SD*	*N*
Male	Control	59.81	25.19	42
	Autism	82.81	22.80	102
Female	Control	63.94	23.74	140
	Autism	88.42	22.73	164

Table 8.15 Participant descriptives for the Intolerance of Uncertainty Scale (IUS) within the full sample. Mean, standard deviation (*SD*) and sample size (*N*) are shown for all subgroups after stratifying based on sex and diagnosis.

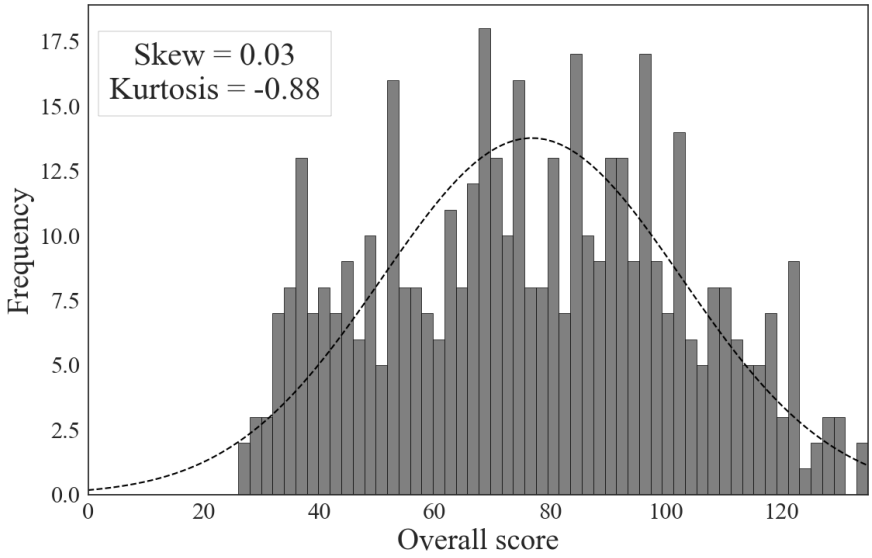


Fig. 8.24 Frequency distribution of scores on the Intolerance of Uncertainty Scale (IUS) across all participants. The dotted line shows a kernel density estimate of a normal Gaussian distribution (skew and kurtosis = 0) based on the mean and variance of the sample.

Age effects

Participants' scores were plotted against their age at time of the study for all individuals as shown in figure 8.25. The Pearson's test found that the correlation between scores on the IUS and participants' ages failed to reach nominal significance (r = -0.01, $p > 0.3$).

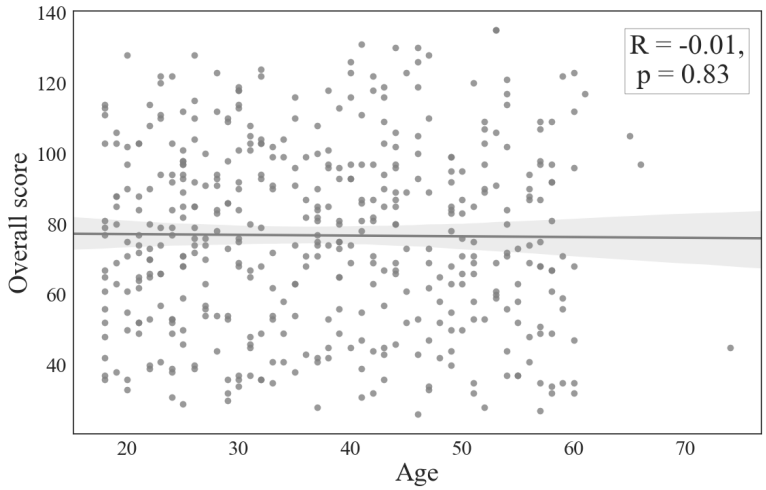


Fig. 8.25 Overall score on the Intolerance of Uncertainty Scale (IUS) plotted against participants age.

Diagnosis and sex effects

A 2-way ANOVA was conducted with scores on the IUS as the outcome measure and diagnostic status and sex as the 2 independent variables. Type III Sum of Squares was used to reduce any potential influence from the imbalance of males and females between the autism and control groups. There was a significant effect of diagnostic status which remained significant after correcting for multiple testing ($F(1, 444) = 88.62$, $p < 0.001$, $\eta^2 = 0.165$).

Cases	Sum of Squares	*df*	Mean Square	*F*	*p*	η^2
Sex	2024.90	1	2024.90	3.729	0.054	0.007
Diagnosis	48118.71	1	48118.71	88.623	< .001	0.165
Sex * Diagnosis	46.35	1	46.35	0.085	0.770	0.000
Residual	241073.45	444	542.96			

Table 8.16 Results from the 2-way ANOVA run on the full sample. Scores on the Intolerance of Uncertainty Scale (IUS) were used as the outcome measure and diagnostic status and sex were used as the 2 independent variables.

There was neither a significant effect of sex ($F(1, 444) = 3.73$ $p = 0.054$, $\eta^2 = 0.007$) or significant interaction between diagnostic status and sex ($F(1, 444) = 0.085$, $p > 0.3$, $\eta^2 = 0.000$, see table 8.16). There was very strong evidence to suggest that diagnostic group had a significant effect on IUS scores ($BF_{inclusion} > 1000$) and there was weak evidence in support of a lack of a direct effect of sex and interaction effect between sex and diagnosis

($BF_{inclusion} = 0.74$ and $BF_{inclusion} = 0.34$ respectively). The results suggest that there is no evidence to suggest a direct or interaction effect of sex in the sample (see figure 8.26).

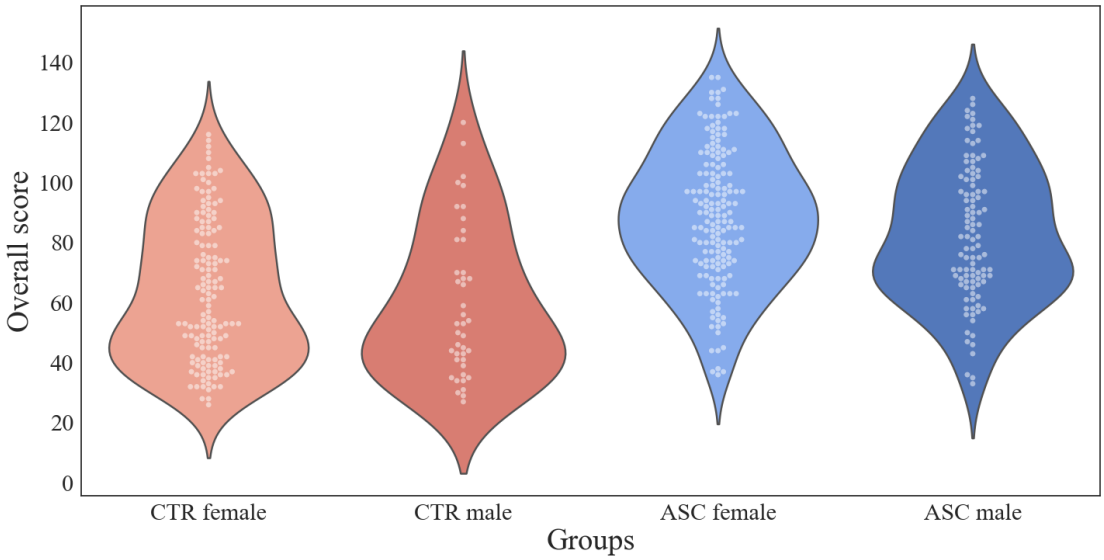


Fig. 8.26 Distributions of overall scores on the Intolerance of Uncertainty Scale (IUS). Individual data points are overlaid on top of violin plot outlines showing the kernel probability density. Data are shown for all subgroups after stratifying based on sex and diagnosis.

8.4 Discussion

In this chapter, I conducted a series of analyses to look for effects of diagnostic status across 8 different questionnaire measures thought to be associated with aspects of autism. There was a significant effect of diagnostic status across all 8 measures, suggesting that each of the measures included here capture part of the autism phenotype. There was a range of effect sizes across the different measures, ranging from the small effect of diagnosis on scores on the EQ ($\eta^2 = 0.035$) to the large effect of diagnosis on scores on the GSQ ($\eta^2 = 0.243$), with the IUS ($\eta^2 = 0.165$) showing a medium sized effect (classification of η^2 effect sizes are based on the criteria suggested by the Open Science Collaboration (Collaboration, 2015)). The focus of the subsequent chapters in this section will be to explore the underlying mechanisms that influence scores on these measures as well as the relationship between these different measures.

The additional aim of this chapter was to determine whether there were any potentially confounding effects of age or sex, due to the fact that both age and the sex-ratio (the relative

proportion of males to females) were found to differ between the autistic individuals and non-autistic controls in the sample. The potential confounding effect of age was not particularly problematic across the various measures as a whole. Age was found to correlate nominally with scores on the AQ and SQ ($r = .12$ and $r = .1$ respectively). As 8 different tests for the effect of age were carried out across all the measures, a Bonferroni correction was applied, leading to neither of these measures correlating significantly with age at the correct significance level. Nonetheless, further consideration should be taken with both of these variables as an extra precaution.

Reports in the literature suggest that there is no correlation between scores on the AQ and age. Ruzich et al. (2015) found no meaningful effect of age on the AQ in a sample of half a million people. Some studies do report a significant effect of age on scores on the SQ (Abbott et al., 2018). Interactions between these two variables and age could be explored by entering additional interaction terms to the exploratory regression model in the following chapter. However, as it appears that it is unlikely for age to have a true effect on scores on the AQ, no further steps need to be taken in the final chapter of this section in which AQ Scores will be used in a number of mediation models. The results only found a significant effect of sex on one of the questionnaire measures, the ZAS. The interaction between sex and scores on this measure could be explored in the following chapter by entering it as an additional interaction term in the exploratory regression model. Further, steps should be taken to ensure that the unbalanced sex ratios are not driving any effects in mediation analyses, conducted in the final chapter of this section, that include anxiety as a part of the model.

Chapter 9

Cognitive mechanisms of intolerance of uncertainty in autism

Overview

This chapter presents an examination of intolerance of uncertainty as a psychological construct and its relationship to the questionnaire measures introduced in the previous chapter. A number of different linear models are considered and contrasted to understand the factors that contribute to variability in attitudes towards uncertainty.

9.1 Background

In the previous chapter, 8 different questionnaires measures were identified in which group differences were found between autistic and non-autistic individuals. Of these measures, the one which is of particular interest to the focus of this thesis is the Intolerance of Uncertainty Scale. A number of recent studies have reported associations between intolerance of uncertainty and other clinical and psychological constructs. Of the 7 other questionnaire measures considered in chapter 8, many of these had previously been associated with intolerance of uncertainty in the literature and are likely to be linked in some way to intolerance of uncertainty. While some of the other measures included in chapter 8 have not previously been directly linked to intolerance of uncertainty, there are findings from the literature which suggest they might be linked and thus warrant further investigation of possible associations.

Anxiety has been strongly linked with intolerance of uncertainty in a number of studies (Carleton, 2012). This relationship has been shown both in the typically developing population (Buhr and Dugas, 2006) as well as in autistic children (Boulter et al., 2014; Neil et al., 2016) and adults (Maisel et al., 2016). Sensory issues have also been linked to intolerance of uncertainty both in typical and autistic samples (Neil et al., 2016; Wigham et al., 2015). It is likely there is an interaction between these 3 constructs, as anxiety has been reported to play a role in the association between sensory issues and intolerance of uncertainty (Neil et al., 2016). It may be the case that high levels of intolerance of uncertainty drive actions to decrease the amount of uncertainty in the environment, which may lead to symptoms of anxiety such as worrying about potential adverse outcomes. Anxiety itself can drive attentional biases to threats and push an individual into a hypervigilant state. This in turn could increase awareness and susceptibility to being negatively affected by sensory stimuli (Green and Ben-Sasson, 2010). Conversely, it is also possible that increased sensory sensitivity could cause both intolerance of uncertainty and anxiety.

Alexithymia was another construct for which a measure was included in this study. Previous reports have found elevated rates of alexithymia in autism (Gaigg et al., 2018) and this was supported by the results in chapter 8. Alexithymia has also been found to correlated with intolerance of uncertainty (Maisel et al., 2016). Further, intolerance of uncertainty has also been shown to be increased in individuals with obsessive-compulsive disorder relative to healthy controls (Gillett et al., 2018; Tolin et al., 2003) and has been associated with the level to which non-clinical individuals display obsessive or compulsive behaviours (Dugas et al., 2001).

The Autism Spectrum Quotient, Empathy Quotient and Systemising Quotient-Revised are 3 measures designed to assess an individual's relative degree of autistic traits, empathetic thoughts and systematic attitudes respectively. The Autism Spectrum Quotient has previously been shown to correlate with scores on the Intolerance of Uncertainty Scale (Maisel et al., 2016). This result is in line with reports of elevated levels of intolerance of uncertainty in autistic individuals as the underlying etiology of autism and variation of autistic traits are thought to be similar (Ronald and Hoekstra, 2011). Intolerance of uncertainty has not been reported to be directly associated with either the Empathy Quotient or the Systemising Quotient-Revised. However, there are suggestions from other areas of the literature that both of these measures may be linked to intolerance of uncertainty.

Intolerance of uncertainty has been found to correlate with emotional dysregulation, which refers to the occurrence of poorly modulated emotional responses (Vasa et al., 2018). As empathy is involved in processing and interpreting the emotions of others, it is likely to be involved in emotional self-regulation as well (Gross, 1999; Schipper and Petermann,

2013). Further, functioning for both empathy and processing of uncertainty have been linked to similar regions of the brain such as the insular cortex (Singer et al., 2009). Similarly for systemising, while it has not been shown to be directly associated with intolerance of uncertainty there are reasons to believe an association might exist. Insistence on sameness, which is thought to be strongly related to intolerance of uncertainty (Black et al., 2017; Uljarević et al., 2017), is a feature of autism linked to hyper-systemising (Baron-Cohen et al., 2005). Therefore, there are reasons to think both empathy and systemising may be associated with intolerance of uncertainty.

While there have been a number of reports of different associations between the various measures mentioned and intolerance of uncertainty, these findings are fragmented across different studies. This makes it difficult to assess the relative strengths of associations between the different predictors of intolerance of uncertainty. The present chapter will examine the relationship between the Intolerance of Uncertainty Scale and the other 7 measures described in chapter 8. This will allow for the relative strength of the different associations to be evaluated and will also make it possible to test whether each of these associations exist separately of the effects of other predictors. Carrying out an analysis of this nature will lead to a better understanding of intolerance of uncertainty as a psychological construct, as it allows for it to be understood in terms of its relation to other well-known psychological and clinical concepts.

9.2 Methods

The final sample described in chapter 8 (following the data cleaning steps detailed) was used for the analysis in this chapter. All autism and control participants were included as the analysis focused on the relationships between variation in the different measures rather than group differences. As the aim of this analysis was to explore the relationship of intolerance of uncertainty with other features of autism, the dataset was not split into training and testing sets. While a data splitting approach would traditionally be taken when developing a predictive model, the focus of the present analysis was to gain a better understanding of intolerance of uncertainty as a psychological construct and not specifically to develop a predictive model. Therefore, to maximise statistical power all participants were included during the main analyses.

An exploratory model was developed by fitting a linear model to subjects' scores on the Intolerance of Uncertainty Scale (IUS). A stepwise backward elimination approach was used to refine the model by attempting to minimise AIC values while increasing the proportion of variance explained by the model. For each step following the initial state of the model,

the independent variable with the largest p-value was removed from the model and the new model was assessed for quality. Adjusted R^2 values were used alongside AIC values to determine whether the model had improved after each step taken as well as for general comparison across models (Anderson and Burnham, 2006; Burnham and Anderson, 2004). Adjusted R^2 values were used instead of standard R^2 values in order to avoid issues with overfitting. The model is initiated with a set of terms and the term with the largest p-value is removed before running the model again. For the backward elimination process to continue, one of two criteria had to be met: either (i) the AIC value had decreased and the R^2 value had increased or stayed the same or (ii) the AIC value had stayed the same and the R^2 value had increased. If neither of these criteria were met then the model returned to the previous step and the process was terminated. Otherwise, the process was repeated for the next step by removing the next independent variable with the greatest p-value and repeating the process.

The initial model included diagnostic status, sex, age and all 7 of the other questionnaire measures. As all measures had previously been found to have significant effects of diagnostic status, additional interaction terms were included between the questionnaire measures and diagnostic status. Normality assumptions for all measures have been evaluated in chapter 8 and were considered satisfactory for all variables, so standard parametric testing was used. Interaction terms were also included between age and both Systemising Quotient-Revised (SQ) and Autism Spectrum Quotient (AQ) based on the results in chapter 8. Similarly, a final interaction term was included between Zung Self-rating Anxiety Scale (ZAS) scores and sex.

9.3 Results

9.3.1 Item correlations

Correlations between all the questionnaire item based non-interaction terms (excluding age, sex and diagnosis) were plotted to assess dependencies across these variables (figure 9.1). Scores on the IUS showed a strong correlation with scores on the Obsessive-Compulsive Inventory-Revised (OCI), the Toronto Alexithymia Scale-II (TAS), the Glasgow Sensory Questionnaire (GSQ) and the ZAS. Weak correlations were found between the IUS and the AQ, Empathy Quotient (EQ) and SQ (classification of correlation sizes were taken from the Open Science Collaboration (Collaboration, 2015)). There were a number of strong correlations between other pairs of variables which suggested there may potentially be issues with multicollinearity when testing models.

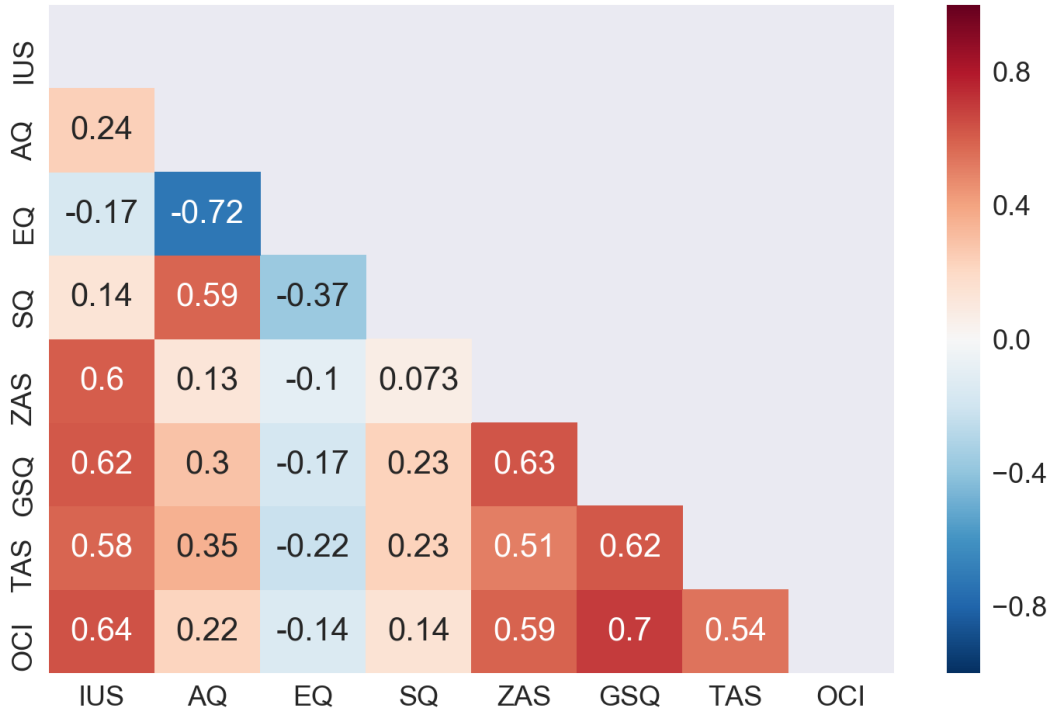


Fig. 9.1 Correlation matrix showing the Spearman correlations for all pairs of questionnaire measures. The shade of each box in the matrix indicates the strength of the correlation, with stronger correlations shaded darker and weaker correlations shaded lighter. The colour of each box shows the direction of correlation, with red indicating a positive correlation and blue indicating a negative correlation.

9.3.2 Model 1

The initial model included the 20 predictor variables detailed in the methods section. All variables and their coefficients in the initial model are summarised in table 9.1.

	coef	std err	t	P>|t|
Intercept	20.4564	15.291	1.338	0.182
Diagnosis	-0.3823	17.023	-0.022	0.982
Age	-0.0909	0.237	-0.384	0.701
Sex	6.2240	8.325	0.748	0.455
AQ	-0.4644	0.363	-1.280	0.201
EQ	-0.1253	0.113	-1.106	0.269
SQ	0.0842	0.165	0.512	0.609
ZAS	0.4175	0.270	1.546	0.123
GSQ	0.2083	0.103	2.013	0.045
TAS	0.4741	0.147	3.235	0.001
OCI	0.4344	0.196	2.219	0.027
Diagnosis*AQ	0.5275	0.327	1.613	0.108
Diagnosis*EQ	0.2874	0.206	1.398	0.163
Diagnosis*SQ	-0.0983	0.108	-0.910	0.363
Diagnosis*ZAS	0.2988	0.270	1.106	0.270
Diagnosis*GSQ	-0.1393	0.127	-1.097	0.274
Diagnosis*TAS	-0.3006	0.188	-1.597	0.111
Diagnosis*OCI	0.1341	0.227	0.590	0.556
Age*AQ	0.0054	0.008	0.656	0.512
Age*SQ	-0.0012	0.004	-0.284	0.776
Sex*ZAS	-0.1308	0.199	-0.656	0.512

Table 9.1 Summary of predictor variables for the initial state of model 1.

This initial model explained 52.5% of the variance (see table 9.2). While this is a fairly substantial amount of variance to explain, within the area of psychological constructs, the model is far from refined and tells us very little about the underlying structure of IUS and how it may relate to other features of the autism phenotype. A stepwise backward selection process was used to refine the model as detailed in the methods section.

R-squared:	0.553
Adj. R-squared:	0.525
F-statistic:	19.79
Prob (F-statistic):	1.41e-44
Log-Likelihood:	-1451.9
AIC:	2946.
BIC:	3026.

Table 9.2 Model characteristics for the initial state of model 1.

Model descriptives

The model settled upon by the backward selection process contained 5 independent predictors, having removed 14 of the 20 initial variables in the model. Age and sex were removed from the model, as well as the interaction terms for both variables. From the questionnaire models, the AQ, EQ and SQ were all removed. Diagnostic status (Diagnosis) and 4 of the questionnaire measures (ZAS, GSQ, TAS and OCI) remained in the model, as well as an interaction term between Diagnosis and TAS. This model is summarised in table 9.3.

	coef	**std err**	**t**	**P>|t|**
Intercept	7.9870	6.147	1.299	0.195
Diagnosis	20.2959	8.551	2.374	0.018
ZAS	0.5592	0.124	4.523	0.000
GSQ	0.1050	0.058	1.818	0.070
TAS	0.4951	0.121	4.104	0.000
OCI	0.5106	0.098	5.223	0.000
Diagnosis*TAS	-0.2743	0.148	-1.847	0.066

Table 9.3 Summary of predictor variables in the final refined version model 1.

While the model contains two non-significant terms, GSQ and the interaction term between Diagnosis and TAS, the removal of these had a negative effect on both the AIC score and Adjusted R^2 value. Therefore, both terms were left in the model.

This model explained 53.4% of the variance within IUS scores across 4 dependent variables. This was an improvement on the initial model. The new model also reduced the AIC value by 20, suggesting it is much more suitable than the initial model. Model characteristics are shown in table 9.4. Further steps in the regression (additional removal of variables) reduced the adjusted R^2 value and increased AIC, suggesting that this was an appropriate end point for the final model.

R-squared:	0.542
Adj. R-squared:	0.534
F-statistic:	65.83
Prob (F-statistic):	1.04e-53
Log-Likelihood:	-1456.2
AIC:	2926.
BIC:	2953.

Table 9.4 Model characteristics for model 1.

The plot of the fitted values against scores on the IUS shows the fit of the model (figure 9.2). Values for subjects from the autistic and non-autistic group are plotted separately. The slopes were similar for both groups, suggesting that the model predicted IUS scores equally well across the two groups.

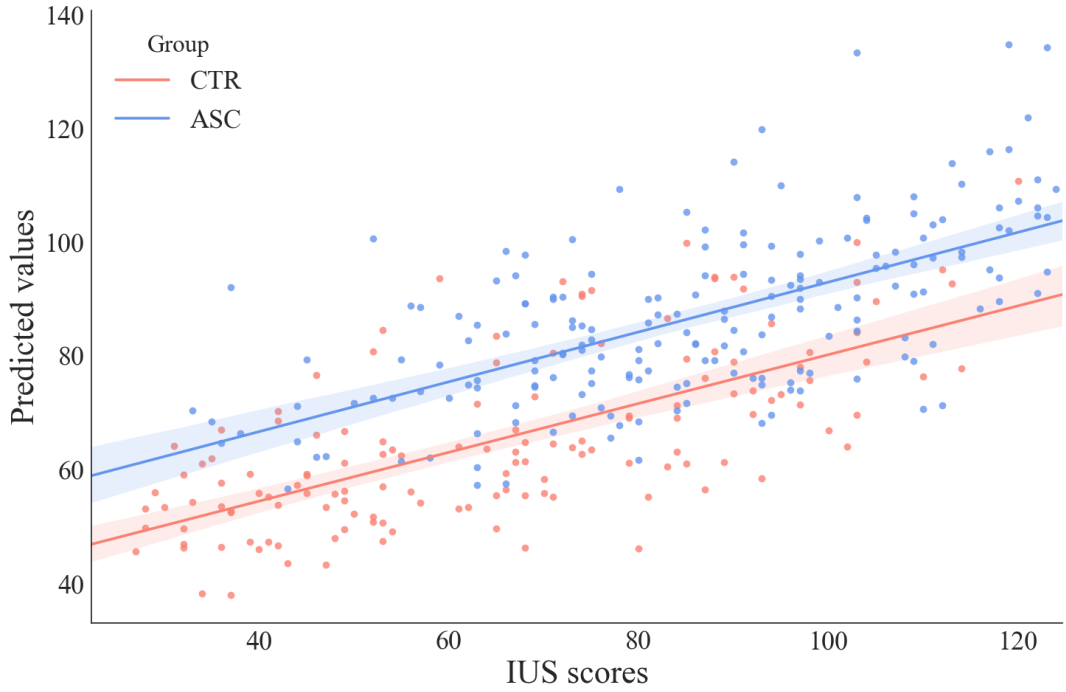


Fig. 9.2 Fitted values from the model plotted against observed scores on the Intolerance of Uncertainty Scale (IUS) for participants in the control (CTR) and autism (ASC) groups.

Partial regression plots were plotted for all predictors in the model to show the individual effect of adding each respective variable to a model (figure 9.3). These figures plot the residuals that come from regressing the outcome variable against all the predictors except the specific variable in question against the residuals that come from regressing the specific

variable in question against all other predictors. Non-zero slopes indicate that the variable in question has a significant effect on the model. This was observed for all variables in the model, supporting their inclusion. The plots for Diagnosis, GSQ and Diagnosis * TAS terms had smaller slopes relative to the other terms, suggestion that these predictors were not as influential on the model.

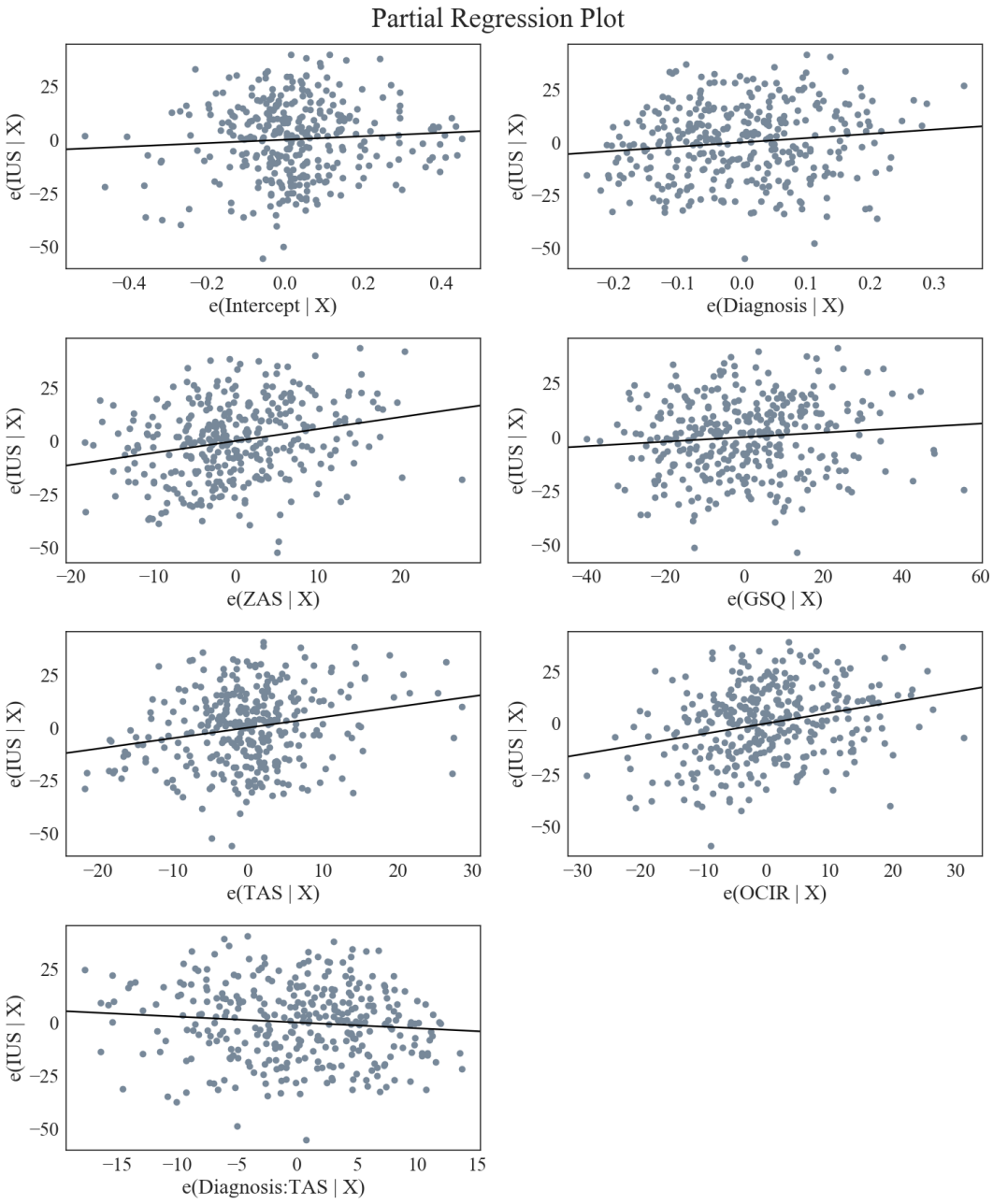


Fig. 9.3 Partial regression plot for all variables in model 1.

High influence cases

The overall influence of individual data points on the model were then considered. An influence plot was created for all individual participants, showing the studentised residuals against the leverage values (figure 9.4). The relative influence of each data point is represented by the size of the dot on the plot. In total, 31 cases were found to have particularly high influence on the model. High influence points are coloured grey, with orange borders indicating a data point with a large residual and red borders indicating a case with high leverage. 10 of these had large studentised residuals and the other 21 had high leverage. The model was run again on a sample in which these cases had been removed. The updated model characteristics are summarised in table 9.5. The model was able to explain a higher proportion of the variance in the new sample and the AIC value reduced by a significant amount ($\Delta_{AIC} = 212$).

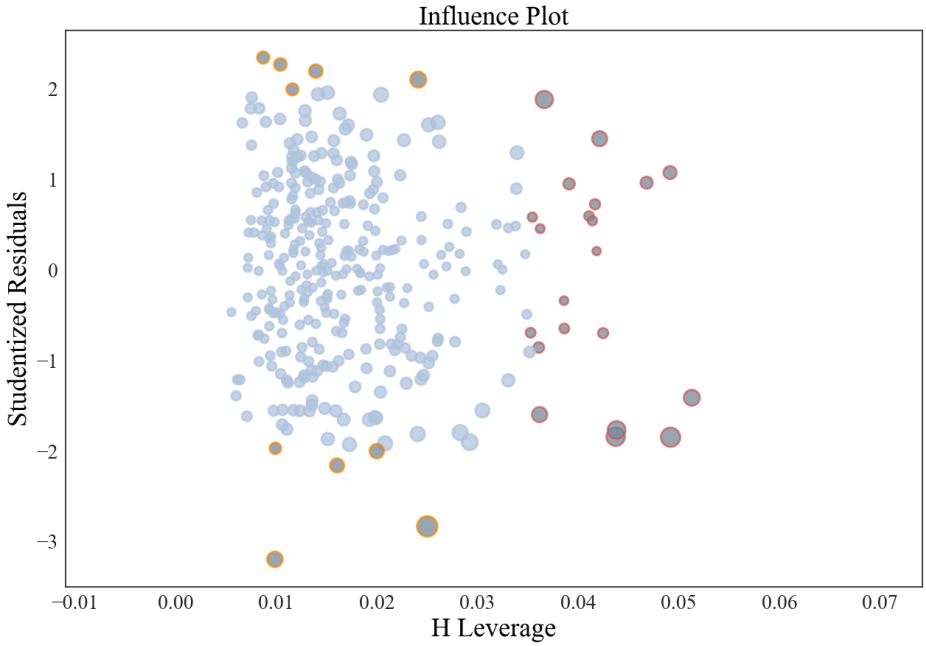


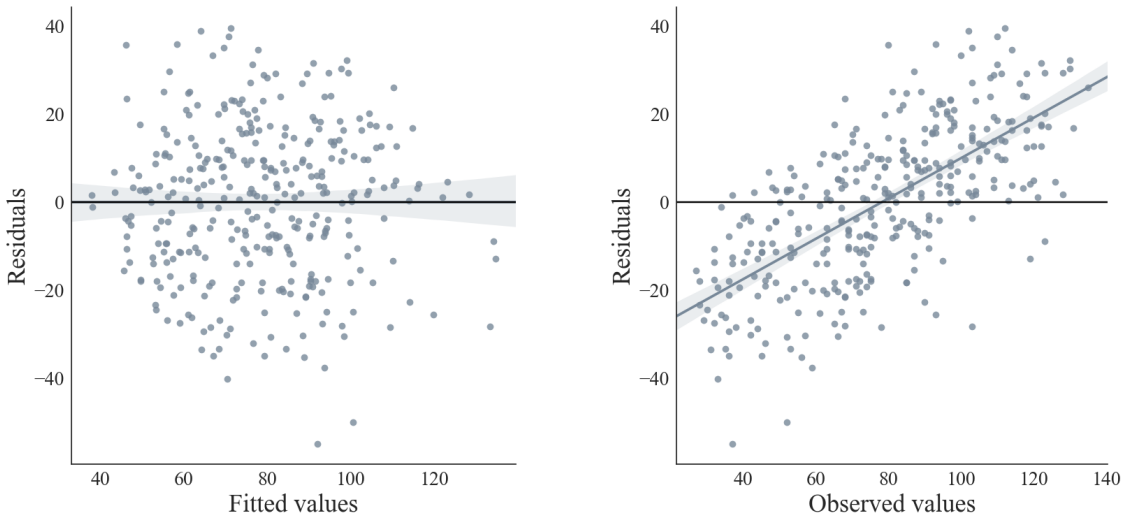
Fig. 9.4 Influence plot for model 1 showing studentised residuals against leverage for all participants. High influence points are coloured grey, with orange borders showing cases with large residuals and red borders showing cases with high leverage.

R-squared:	0.552
Adj. R-squared:	0.544
F-statistic:	63.78
Prob (F-statistic):	2.84e-51
Log-Likelihood:	-1350.0
AIC:	2714.
BIC:	2740.

Table 9.5 Model characteristics for model 1 after removal of high influence cases.

Residual plots

Finally, the studentised residuals were plotted against the fitted values (predicted model scores) and observed values (IUS scores) for all participants (figure 9.5 (a) and (b) respectively). The plot of residuals against fitted values showed an approximately random distribution, suggesting that the assumptions for regression were largely met. The plot of residuals against the observed values showed a clear positive correlation, suggested a proportion of the variance was not satisfactorily explained in the model. This result suggests that an additional construct may influence IUS that is not included in the present model.



(a) (b)

Fig. 9.5 Studentised residuals for model 1 plotted against (a) fitted values (predicted model scores) and (b) observed values (IUS scores) for all participants.

Summary

While the model described here was satisfactory on many levels, two additional models were explored based on the results discussed above. Each of these two models would respectively take a more exploratory and more conservative approach to including predictor terms. Firstly, because of the unexplained variance in the model, an additional exploratory model with various additional interaction terms was explored using a stepwise backward selection approach (model 2). Secondly, due to the high correlations between some of the predictor terms in model 1, a more conservative model would also be explored by forcing the stepwise backward selection past the termination point established in model 1 to assess how simpler models perform in comparison (model 3).

9.3.3 Model 2

The second model started off with all the terms included in model 1 with 6 additional predictor variables. These additional predictor terms consisted of interaction terms for all pairs of predictor variables which were strongly correlated (see figure 9.1). This is based on the assumption that high collinearity between predictor variables is suggestive of potentially meaningful interaction effects (Faraway, 2002). All variables and their coefficients in the initial model are summarised in table 9.6. Again, a stepwise backward selection process was

used to refine this initial model using adjusted R^2 and AIC values to determine whether the model improved after each step.

	coef	std err	t	P>|t|
Intercept	9.6348	16.490	0.584	0.559
Diagnosis	12.9662	11.412	1.136	0.257
ZAS	0.2896	0.542	0.534	0.594
GSQ	0.0281	0.275	0.102	0.919
TAS	0.5506	0.362	1.519	0.130
OCI	1.1355	0.543	2.092	0.037
Diagnosis*TAS	-0.1604	0.195	-0.823	0.411
ZAS*GSQ	0.0108	0.006	1.704	0.089
ZAS*TAS	0.0011	0.010	0.116	0.908
ZAS*OCI	-0.0231	0.011	-2.168	0.031
GSQ*TAS	-0.0055	0.004	-1.268	0.206
GSQ*OCI	-0.0022	0.004	-0.589	0.556
TAS*OCI	0.0092	0.008	1.079	0.281

Table 9.6 Summary of all initial predictor variables included in initial state of model 2.

The unrefined model explained 53.4% of the variance (see table 9.7). This was not an improvement on the amount of variance explained by model 1 and had a larger AIC value. A backward selection process was carried out on the additional model terms that had been added to model 1.

R-squared:	0.551
Adj. R-squared:	0.534
F-statistic:	33.53
Prob (F-statistic):	5.45e-50
Log-Likelihood:	-1452.7
AIC:	2931.
BIC:	2981.

Table 9.7 Model characteristics for the initial state of model 2.

Model descriptives

After carrying out the backward selection process, the model settled upon contained 2 additional terms to model 1. These were an interaction term between ZAS * GSQ and an interaction term between ZAS * OCI. This model is summarised in table 9.3.

	coef	std err	t	P>|t|
Intercept	8.8627	9.780	0.906	0.365
Diagnosis	17.3188	8.933	1.939	0.053
ZAS	0.5827	0.263	2.213	0.028
GSQ	-0.1532	0.213	-0.719	0.473
TAS	0.4609	0.124	3.716	0.000
OCI	1.3200	0.418	3.159	0.002
Diagnosis*TAS	-0.2289	0.154	-1.483	0.139
ZAS*GSQ	0.0061	0.005	1.227	0.221
ZAS*OCI	-0.0184	0.009	-1.981	0.048

Table 9.8 Summary of final predictor variables included in the refined version of model 2.

This model explained 53.7% of the variance within IUS scores. This was a slight improvement on both the initial state of model 2 and final state of model 1. The new model matched the AIC value of model 1, suggesting the slight increase in the proportion of variance explained was not at the cost of a reduced quality in the model. Model characteristics are shown in table 9.9. Further steps in the regression (additional removal of variables) reduced the adjusted R^2 value and had no effect on AIC, suggesting that this was a good end point for the final model.

R-squared:	0.548
Adj. R-squared:	0.537
F-statistic:	50.21
Prob (F-statistic):	8.92e-53
Log-Likelihood:	-1454.0
AIC:	2926.
BIC:	2961.

Table 9.9 Model characteristics for the final refined version of model 2.

Partial regression plots were plotted for all predictors in the model to check the individual effects of adding the new terms to the model (figure 9.6). The plot for ZAS * OCI showed a steeper slope, suggesting this term had a greater influence on the model than the ZAS * GSQ term. Additionally, the inclusion of these additional terms led to a change in the direction of the relationship between the two residual terms in the partial regression plot for GSQ. This brings into question whether the direct GSQ term has a true effect on the model or whether it's influence occurs indirectly through an interaction with a separate predictor.

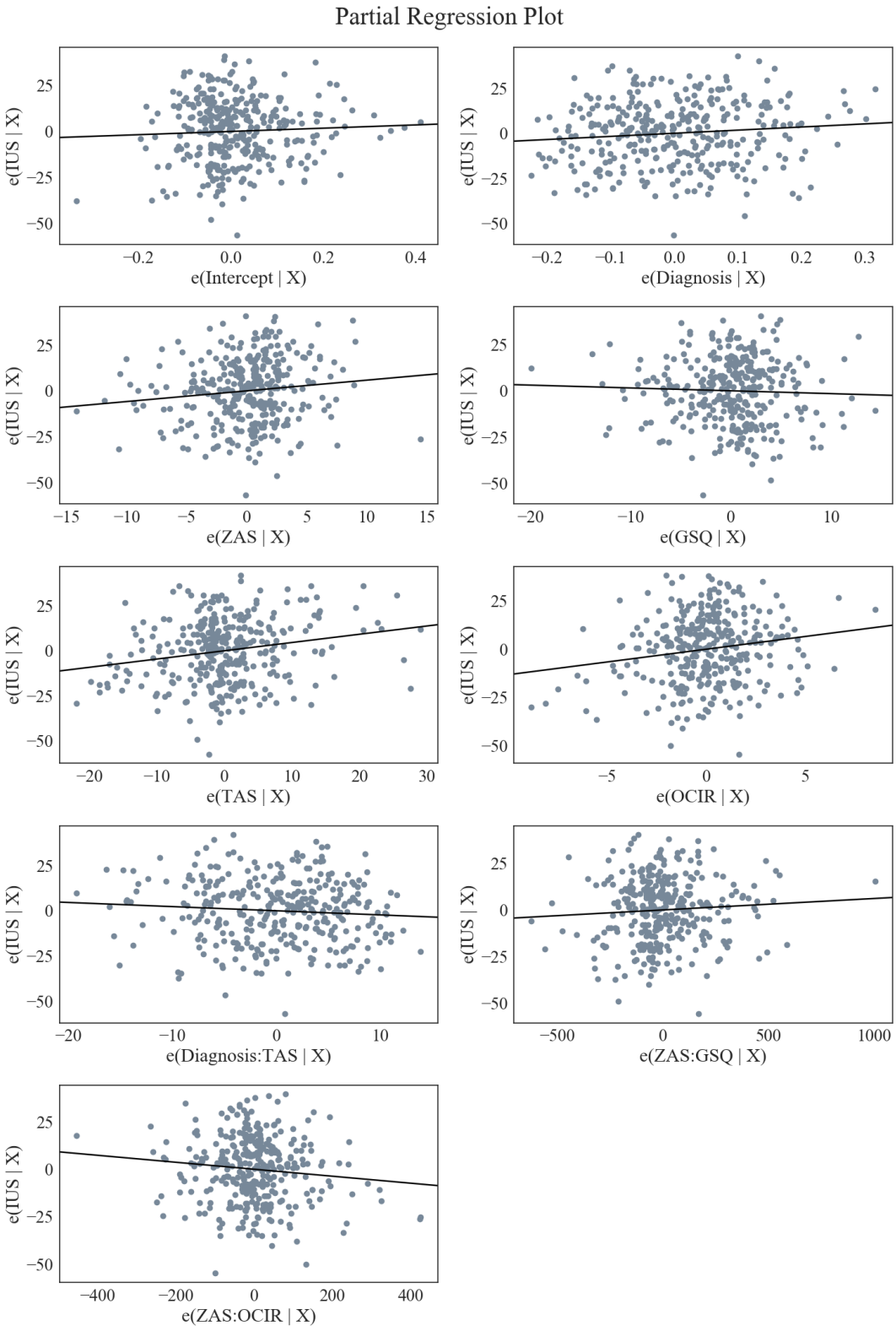


Fig. 9.6 Partial regression plot for all variables in the final version of model 2.

High influence cases

An influence plot was again used so the overall influence of individual data points on the model participants could be assessed (figure 9.4). The relative influence of each data point is represented by the size of the dot on the plot.

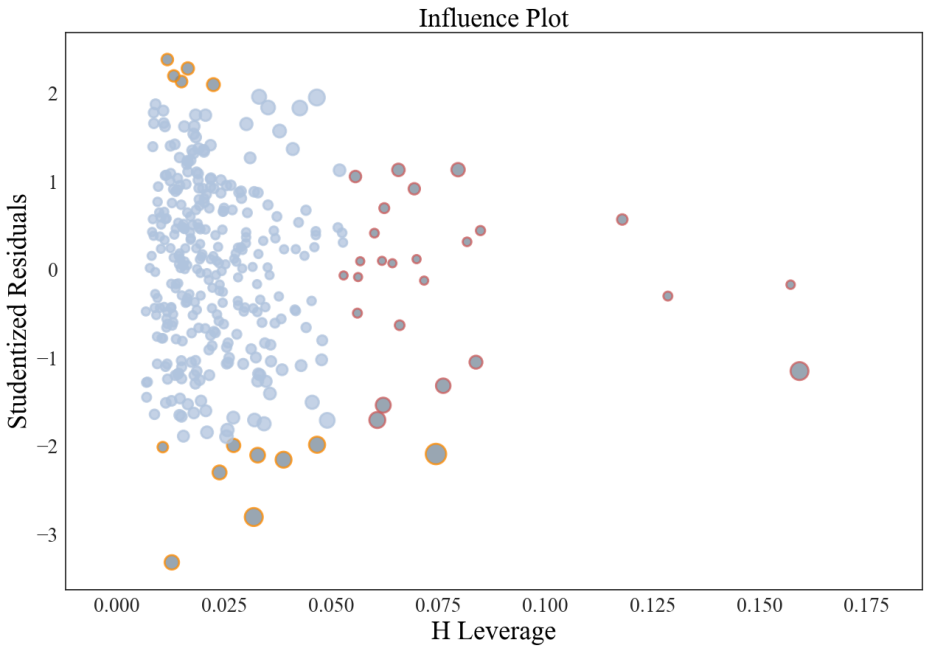


Fig. 9.7 Influence plot for model 2 showing studentised residuals against leverage for all participants. High influence points are coloured grey, with orange borders showing cases with large residuals and red borders showing cases with high leverage.

High influence points are indicated by colouring them grey, with orange borders indicating large residual and red borders indicating high leverage. Overall, 39 cases were found to have particularly high influence on the model. 13 of these had large studentised residuals, 25 had high leverage and one case had large residuals and high leverage.

The model was run on the sample after removing these cases. The updated model characteristics are summarised in table 9.10. The model explained a higher proportion of the variance in the new sample (55.2%) and the AIC value was significantly reduced ($\Delta_{AIC} = 229$).

R-squared:	0.564
Adj. R-squared:	0.552
F-statistic:	49.45
Prob (F-statistic):	8.19e-51
Log-Likelihood:	-1339.4
AIC:	2697.
BIC:	2731.

Table 9.10 Model characteristics for model 2 after removal of high influence cases.

9.3.4 Model 3

The third and final model was aimed at reducing model 1 further, by continuing past the previous stopping point of the stepwise regression approach. The model started off with all the terms included in model 1 (see table 9.3). The stopping criteria for this model was defined as either a significant (> 10%) reduction in the adjusted R^2 value or increase in the AIC value.

Model descriptives

After continuing the backward selection process passed the previous stopping point, the model settled upon a reduced model with the removal of the GSQ term and the Diagnosis * TAS interaction term. Further removal of variables led to a much greater reduction in the adjusted R^2 value and a large increase in AIC value, suggesting that this was a good end point for the final model. This model is summarised in table 9.11.

	coef	**std err**	**t**	**P>|t|**
Intercept	15.0955	4.734	3.189	0.002
Diagnosis	6.5921	2.265	2.910	0.004
ZAS	0.6388	0.118	5.420	0.000
TAS	0.3700	0.085	4.348	0.000
OCI	0.5789	0.091	6.392	0.000

Table 9.11 Summary of predictor variables included in the final state of model 3.

This model explained 52.7% of the variance within IUS scores. This was only a modest reduction from the performance of models 1 and 2. The slight increase in AIC value suggests a small reduction in the quality in the model. Model characteristics are shown in table 9.12.

R-squared:	0.532
Adj. R-squared:	0.527
F-statistic:	95.58
Prob (F-statistic):	3.31e-54
Log-Likelihood:	-1459.7
AIC:	2929.
BIC:	2949.

Table 9.12 Model characteristics for the final state of model 3.

Partial regression plots were plotted for all predictors in the model to check the individual effects of adding the new terms to the model (figure 9.8). The plots indicated that all of the 3 questionnaire based predictors had a strong effect on the model, with diagnosis appearing to have a more modest effect.

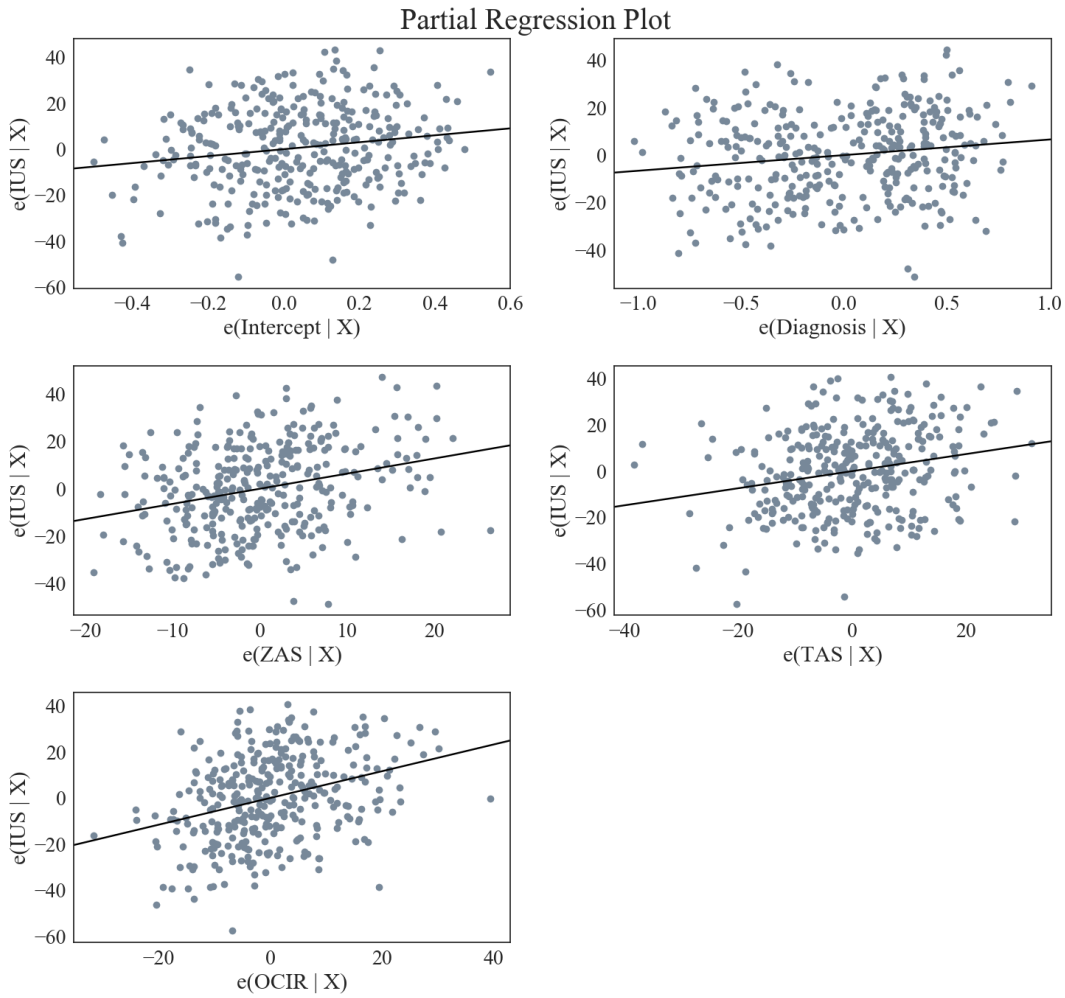


Fig. 9.8 Partial regression plot for all variables in model 3.

High influence cases

An influence plot was again used to assess the influence of individual data points on the model (figure 9.9). Overall, 30 cases were found to have particularly high influence on the model. 9 of these had large studentised residuals, 20 had high leverage and one case had both large residuals and high leverage.

After removing these cases from the sample, the model was able to explain a higher proportion of the variance (53.2%) and the AIC value was significantly reduced ($\Delta_{AIC} = 187$). The updated model characteristics are summarised in table 9.13.

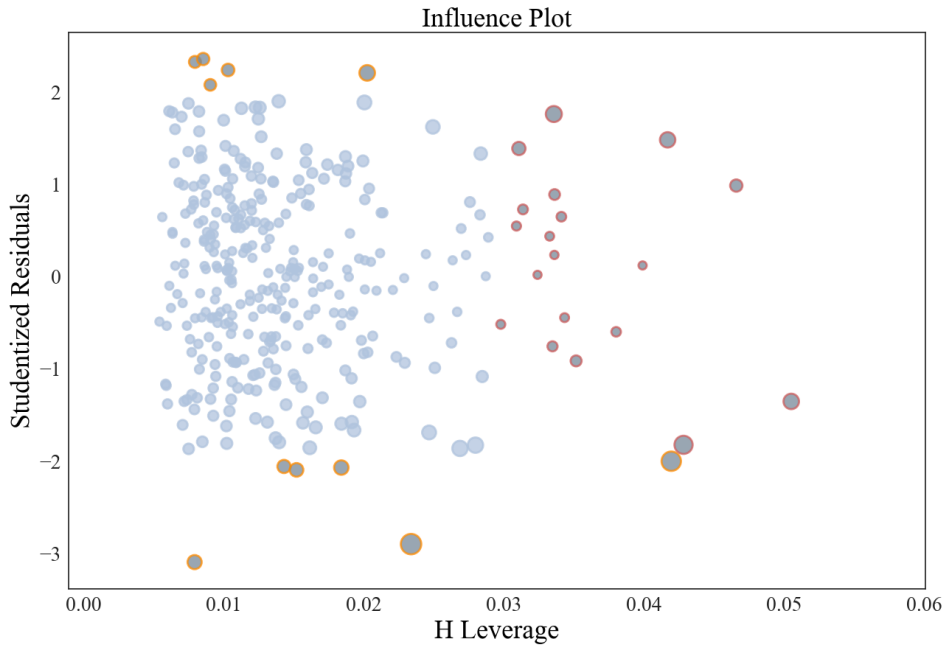


Fig. 9.9 Influence plot showing studentised residuals against leverage for all participants. High influence points are coloured grey, with orange borders showing cases with large residuals and red borders showing cases with high leverage.

R-squared:	0.538
Adj. R-squared:	0.532
F-statistic:	91.27
Prob (F-statistic):	2.17e-51
Log-Likelihood:	-1365.9
AIC:	2742.
BIC:	2761.

Table 9.13 Model characteristics for model 3 after removal of high influence cases.

9.4 Discussion

The purpose of this discussion section is twofold. Firstly, it will focus briefly on a comparison of the 3 models that have been evaluated in the present chapter. Secondly, and most importantly, it will look at what insights can be drawn from the nature of these models regarding the relationship of intolerance of uncertainty to other clinical features associated with autism. An in-depth comparison of the 3 models is not required here as the aim of the analysis was

not to develop a practical predictive model, but to use the approach as a means of exploring the underlying features of intolerance of uncertainty as a psychological construct.

9.4.1 Performance of models

All 3 models performed well and explained a high proportion of the variance within scores obtained on the IUS. The amount of variance explained by each model was very similar, particularly between model 1 (53.4%) and model 2 (53.7%). Model 1 and model 2 had identical AIC values (2926), suggesting the two models were of a similar quality. While model 3 explained a slightly smaller proportion of the variance (52.7%) and had a slightly higher AIC value (2929) than the other models, it was the least complex of all the models.

High influence data points were identified for all 3 models. This was done by considering both leverage and the size of the residuals and calculating Cook's distance (Cook, 1977). For all models, the identified data points were removed from the samples and the models were rerun on the new samples. This allowed for the fit to be separately assessed with and without highly influential cases to determine the degree to which over fitting may have occurred in each model. The smallest changes before and after removing influential cases occurred in model 3. Both the increase in proportion of variance explained ($\Delta_{var} = 0.5\%$) and decrease in AIC scores ($\Delta_{AIC} = -187$) were releatively low, compared to model 1 ($\Delta_{var} = 1.0\%, \Delta_{AIC} = -212$) and model 2 ($\Delta_{var} = 1.2\%, \Delta_{AIC} = -229$). This suggests that model 3 was influenced the least by individual data points and is the most generalisable of the 3 models.

As this final model seemed to be the least likely to be affected by overfitting as well as being the least complex of the 3 models, the second part of the discussion will primarily focus on the 4 terms included in the final model. These 4 variables (Diagnosis, ZAS, OCI and TAS) were able to explain over 50% of the variance in intolerance of uncertainty. However, some consideration will also be given to the additional terms in model 1 and model 2.

9.4.2 Predictors of intolerance of uncertainty

Diagnostic status was a significant predictor of intolerance of uncertainty, in line with reports from previous studies as well as the results from chapter 8. The results indicate that levels of intolerance of uncertainty tend to be higher in autistic adults than in non-autistic adults and support previous research which found similar effects in younger populations (Boulter et al., 2014; Neil et al., 2016).

There was a strong association of intolerance of uncertainty with anxiety, again in line with previous reports from the literature. This association has been found in a number of

studies in children and adolescents (Boulter et al., 2014; Neil et al., 2016; Wigham et al., 2015) as well as one study looking at this relationship in adults (Maisel et al., 2016). The nature of this association will be explored further in the following chapter, by conducting analyses to determine whether intolerance of uncertainty plays a mediating role on the elevated levels of anxiety in autistic adults.

While sensory issues were included as a predictor in the first model, it was unclear whether they directly accounted for a meaningful amount of the variance in intolerance of uncertainty based on examination of the partial regression plots, the non-significant p-value in the first model and the improved performance of the final model after forcing the removal of sensory issues as a predictor. The inclusion of an interaction term between sensory issues and anxiety in the second model reduced the influence of the main sensory issues term. This suggests that sensory issues might correlate indirectly with intolerance of uncertainty through an association with anxiety. This hypothesis will be tested further in the following chapter.

Scores on the OCI were also found to be a significant predictor of intolerance of uncertainty. Unlike the association between anxiety and intolerance of uncertainty, this is not a commonly reported association in the literature. One explanation for this association may be that the OCI also picks up on the repetitive and restricted behaviours that commonly occur in autism (Gjevik et al., 2011). It has been suggested that some of the repetitive or ritualistic behaviours which often feature in autism might be driven by intolerance of uncertainty (Joyce et al., 2017; Wigham et al., 2015). Research has also supported the argument that repetitive behaviours may occur in autism as a strategy to manage anxiety by exerting control over the external environment in order to make it more predictable (Lidstone et al., 2014; Rodgers et al., 2012b). Therefore, this association could be driven by repetitive behaviours co-occurring with intolerance of uncertainty and anxiety, which in turn are picked up by the OCI. The present study was limited in the number of measures which were completed by participants due to concerns with time demands of the study. However, future research could explore this relationship further by including direct measures of restricted and repetitive behaviours such as the Adult Repetitive Behaviours Questionnaire-2 (Barrett et al., 2015).

The association with alexithymia is not as intuitively clear as the other two clinical measures. One possible explanation is that behaviours associated with intolerance of uncertainty and alexithymia are affected by a common area (or areas) of the brain. Alexithymia has been associated with disruption to a number of brain regions, including the insula cortex and anterior cingulate cortex (Kano and Fukudo, 2013). These regions are also involved in processing uncertainty in reward outcomes (Jo and Jung, 2016), updating prediction errors (Ide et al., 2013) and calculating precision of expectations (Behrens et al., 2007). It may be the case that autism might be linked to changes in function in regions of the brain that are

involved in both emotional monitoring and processing uncertainty. This could provide an explanation for the strong association between alexithymia and intolerance of uncertainty that was reported in this chapter. Interestingly, the insula cortex and anterior cingulate cortex are both implicated in autism and atypical functioning and connectivity have been reported in these areas in autistic individuals (Di Martino et al., 2009; Uddin and Menon, 2009).

The approach taken in this chapter was very exploratory and the results presented here should form the basis for further research. As mentioned above, there was a limited number of questionnaire measures included in the present study due to pragmatic limitations. Future research could expand on the analysis presented here by including other questionnaire measures to specifically measure restricted and repetitive behaviours in order to better understand the relationship between intolerance of uncertainty and obsessive-compulsive behaviours. Another construct that could be focused on in future research is depression, which has been linked to intolerance of uncertainty (Cai et al., 2018) and could potentially be involved in the relationship between intolerance of uncertainty and alexithymia (Liss et al., 2008). The next chapter will build upon the results discussed here, by testing a number of specific hypotheses about the relationship between intolerance of uncertainty, anxiety and sensory issues in autism.

Chapter 10

Intolerance of uncertainty, sensory issues and anxiety in autism

Overview

The aim of this chapter is to extend previous work which found associations between intolerance of uncertainty, sensory issues and anxiety in children with and without autism. Specifically, I examined whether these previously reported relationships also exist in the adult population. Mediation analyses were carried out to assess whether the increased levels of intolerance of uncertainty often found in autistic individuals play a role in other clinical features of the condition, namely anxiety and sensory issues.

10.1 Background

The theory that autistic individuals show reduced use of prior information is inherently associated with challenges in processing perceptual information in uncertain environments. The predictive aspects of cognition allow individuals to carry out statistical inference using decision-relevant information taken from sensory information and previous experience (Wyart and Koechlin, 2016). This allows for optimal decisions to be made under conditions of uncertainty (Clark, 2015). An attenuation of this predictive process would therefore be expected to lead to difficulties in coping with uncertain environments and possibly extend to

an aversion towards uncertainty. This point is made by Pellicano and Burr (2012b) and other similar accounts of perception in autism (Brock, 2012; Lawson et al., 2014; van Boxtel and Lu, 2013; Van de Cruys et al., 2014).

One psychological construct that might tap into the nature of this opposition to uncertain environments is 'intolerance of uncertainty', which refers to negative approaches to the way in which information is perceived and responded to in uncertain situations (Buhr and Dugas, 2002). This construct has been used to explain aspects of various conditions such as depression (Dugas et al., 2004), generalised anxiety disorder (Carleton et al., 2012) and social anxiety (Whiting et al., 2014). The Intolerance of Uncertainty Scale is a questionnaire measure that allows for this aversion to uncertainty to be quantified (Freeston et al., 1994). Birrell et al. (2011) identified two primary factors within this questionnaire. These are (i) desire for predictability, by active engagement in seeking certainty, and (ii) uncertainty paralysis, the disruption of cognition and ceasing of actions in the face of uncertainty.

Elevated levels of intolerance of uncertainty have been reported in autistic adolescents when compared to non-autistic controls (Chamberlain et al., 2013). These increased levels of intolerance of uncertainty were accompanied by higher levels of self-reported anxiety within the autistic group. The nature of the relationship between intolerance of uncertainty and anxiety in autism has been investigated in a number of other studies. Boulter et al. (2014) reported that increased scores on the Intolerance of Uncertainty Scale were associated with elevated levels of anxiety in children with and without an autism diagnosis. Similarly to Chamberlain et al. (2013), they found that reported levels of intolerance of uncertainty and anxiety were higher in autistic individuals compared with non-autistic controls. However, Boulter et al. (2014) also reported that diagnostic status no longer significantly predicted anxiety levels once the effect of intolerance of uncertainty on anxiety was controlled for. These results suggest that the elevated levels of anxiety often reported in autistic children (Gillott et al., 2001; Kim et al., 2000; White et al., 2009) may occur as a secondary effect resulting from increased levels of intolerance of uncertainty in autism. Additionally, both anxiety and intolerance of uncertainty have been shown to correlate with sensory over-responsiveness in autistic children (Wigham et al., 2015).

More recently, Neil et al. (2016) set out to replicate the findings reported by Boulter et al. (2014) and to explore the extent to which intolerance of uncertainty and anxiety were related to sensory issues in autistic and non-autistic children. They were able to replicate the results of Boulter et al. (2014), showing that intolerance of uncertainty mediated the relationship between autism diagnosis and elevated levels of anxiety. In addition to replicating this finding, they found that intolerance of uncertainty and anxiety were able to explain a large amount of the variance in sensory sensitivities within their autism sample but only a moderate

amount of the variance sensory sensitivities within their control sample. They also found that intolerance of uncertainty significantly predicted sensory issues after controlling for anxiety, but this result only held in their autism sample and was not present in their control sample.

The studies mentioned above all explored the relationship between intolerance of uncertainty, anxiety and autism in younger individuals, focusing on either child or adolescent populations. As behaviours in autism are known to change over the lifespan, especially during the transition into adulthood (Howlin et al., 2004; Shattuck et al., 2007; Taylor and Seltzer, 2010), it is important that research such as this is extended to be carried out in adult samples. One recent study has conducted a similar analysis in an adult population, however this particular study looked at whether intolerance of uncertainty mediated the relationship between autistic traits and anxiety, rather than the relationship between the presence of an autism diagnosis and anxiety (Maisel et al., 2016). Therefore, the aim of this chapter is to carry out a similar set of analyses to Neil et al. (2016) in the adult sample presented in the chapter 8.

10.2 Methods

To account for possible unwanted effects of sex, due to the imbalance between the autism and control groups, a new sample was created in which the number of control females was reduced so that the sex ratio in the control group matched the autism group. This new sample was created using a stratified random sampling process on the full sample (as described in chapter 8). The new sample contained 64 female controls, 40 male controls, 99 autistic males and 159 autistic females. This led to the male to female ratio being 0.63 in the control group and 0.62 in the autism group. The new sample had a total of 362 participants. Where appropriate, analyses would be conducted initially in the full sample.

The 4 measures used in the present analysis were the Autism Spectrum Quotient (AQ; Baron-Cohen et al., 2001), the Intolerance of Uncertainty Scale (IUS; Buhr and Dugas, 2002), the Zung Self-rating Anxiety Scale (ZAS; Zung, 1971) and the Glasgow Sensory Questionnaire (GSQ; Robertson and Simmons, 2013). All measures are described in detail in chapter 8. It is worth noting that these measures differed from the ones used in the previous studies discussed. Both Boulter et al. (2014) and Neil et al. (2016) used the Spence Children's Anxiety scale (Spence, 1998) to measure anxiety as well as a parent-report version of the IUS (Rodgers et al., 2012a). The Short Sensory Profile (Dunn, 1999) was used to measure sensory sensitivity by Neil et al. (2016). Finally, Maisel et al. (2016) measured anxiety using the State Trait Anxiety Inventory (Spielberger and Sydeman, 1994) and used the same measure of intolerance of uncertainty as the present study.

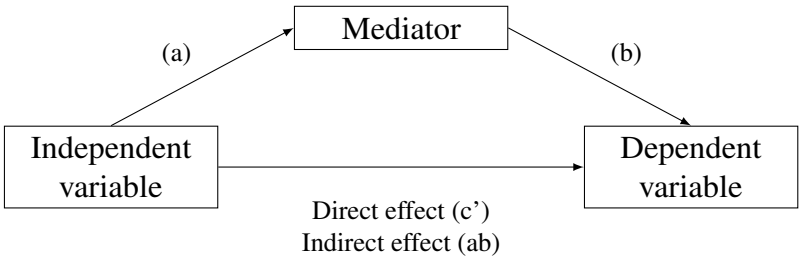


Fig. 10.1 Diagram showing the model used to test for mediation effects. Paths (a) and (b) show the respective assocations of the independent and dependent variables with the mediating variable. Path (c') shows the effect of the independent variable on the dependent variable after controlling for the mediator. Path (ab) shows the estimated indirect effect of the independent variable on the dependent variable through the mediator.

In line with the previous studies cited here, mediation analyses were used to test for possible mediating effects (as shown in figure 10.1). For full mediation to be present, the effect of the independent variable on the dependent variable after controlling for the mediator (c') should be non-significant. In instances where this is not the case, partial mediation may still be present if this path has a weaker correlation after controlling for the mediator. To determine whether partial mediation was present, indirect effects were estimated using bias-corrected and accelerated bootstrapped confidence intervals (based on 1000 samples). These were calculated using the psych package in R (Revelle, 2018). Significance is indicated by these intervals being non-overlapping with zero and p-values were calculated using the Sobel test (Baron and Kenny, 1986).

10.3 Results

10.3.1 Sex-balanced sample

Group differences for scores on the AQ, IUS, ZAS and GSQ for the full sample are all reported in chapter 8. The same procedures that were used to detail the characteristics of the sample across all measures in chapter 8 were carried out here in the sex-balanced sample for the AQ, IUS, ZAS and GSQ.

Autism Spectrum Quotient

Within the sex-balanced sample, 289 participants completed the AQ in full. The average score across all participants was 32.48 (SD = 11.85). Participant descriptives for scores on the AQ are shown in table 10.1.

A Kolmogorov-Smirnov (K-S) test for normality was found to be nominally significant and remained significant after applying a Bonferroni correction to account for multiple testing across the 4 different questionnaire measures that will be used in the analyses presented in this chapter ($D = 0.131$, $p < 0.001$). Due to the oversensitivity of the K-S test in large samples that was discussed previously, the values for the skew and kurtosis of the distribution were evaluated. The skew (-0.77) and kurtosis values (-0.41) for the distribution of scores were not considered problematic.

A Pearson's test found that the correlation between scores on the AQ and participant's ages was nominally significant ($r = 0.13$, $p = 0.03$) but did not remain significant after applying a Bonferroni correction.

Sex	Diagnosis	Mean	*SD*	*N*
Male	Control	25.6	8.63	30
	Autism	35.88	11.73	77
Female	Control	23.25	9.31	52
	Autism	35.75	10.79	130

Table 10.1 Participant descriptives for the Autism Spectrum Quotient (AQ) within the sex-balanced sample. Mean, standard deviation (SD) and sample size (N) are shown for all subgroups after stratifying based on sex and diagnosis.

A 2-way ANOVA was conducted with AQ as the outcome measure and diagnostic status and sex as the 2 independent variable. Type III Sum of Squares was used as detailed in chapter 8. There was a significant effect of diagnostic status which remained significant after correcting for multiple testing ($F(1, 285) = 62.18$, $p < 0.001$, $\eta^2 = 0.178$). There was neither a significant effect of sex ($F(1, 285) = 0.741$, $p > 0.3$, $\eta^2 = 0.002$) or significant interaction between diagnostic status and sex ($F(1, 285) = 0.587$, $p > 0.3$, $\eta^2 = 0.002$, see table 10.2).

Cases	Sum of Squares	*df*	Mean Square	*F*	*p*	η^2
Sex	84.44	1	84.44	0.741	0.390	0.002
Diagnosis	7084.53	1	7084.53	62.177	< .001	0.178
Sex * Diagnosis	66.87	1	66.87	0.587	0.444	0.002
Residual	32473.52	285	113.94			

Table 10.2 Results from the 2-way ANOVA run on within the sex-balanced sample. Scores on the Autism Spectrum Quotient (AQ) were used as the outcome measure and diagnostic status and sex were used as the 2 independent variable.

Intolerance of Uncertainty Scale

Within the sex-balanced sample, 362 participants completed the IUS. The average score across all participants was 79.65 (*SD* = 25.55). Participant descriptives for scores on the IUS are shown in table 10.3.

The K-S test was non-significant ($D = 0.037$, $p > 0.3$). The skew (-0.02) and kurtosis values (-0.81) for the distribution of scores were also not considered problematic.

A Pearson's test found that the correlation between scores on the IUS and participant's ages was non-significant ($r = -0.03$, $p > 0.3$).

Sex	Diagnosis	Mean	*SD*	*N*
Male	Control	59.37	25.27	40
	Autism	83.0	22.70	99
Female	Control	63.97	23.20	64
	Autism	88.98	22.18	159

Table 10.3 Participant descriptives for the Intolerance of Uncertainty Scale (IUS) within the sex-balanced sample. Mean, standard deviation (*SD*) and sample size (*N*) are shown for all subgroups after stratifying based on sex and diagnosis.

A 2-way ANOVA was conducted with IUS as the outcome measure and diagnostic status and sex as the 2 independent variable. Type III Sum of Squares was used as detailed in chapter 8. There was a significant effect of diagnostic status which remained significant after correcting for multiple testing ($F(1, 358) = 78.48$, $p < 0.001$, $\eta^2 = 0.178$). There was neither a significant effect of sex ($F(1, 358) = 3.71$, $p = 0.055$, $\eta^2 = 0.008$) or significant interaction between diagnostic status and sex ($F(1, 358) = 0.064$, $p > 0.3$, $\eta^2 = 0.000$, see table 10.4).

Cases	Sum of Squares	df	Mean Square	F	p	η^2
Sex	1961.37	1	1961.37	3.710	0.055	0.008
Diagnosis	41490.52	1	41490.52	78.484	< .001	0.178
Sex * Diagnosis	33.76	1	33.76	0.064	0.801	0.000
Residual	189256.26	358	528.65			

Table 10.4 Results from the 2-way ANOVA run on within the sex-balanced sample. Scores on the Intolerance of Uncertainty Scale (IUS) were used as the outcome measure and diagnostic status and sex were used as the 2 independent variable.

Zung Self-rating Anxiety Scale

Within the sex-balanced sample, 362 participants completed the ZAS. The average score across all participants was 41.28 (SD = 10.50). Participant descriptives for scores on the ZAS are shown in table 10.5.

The K-S test was nominally significant (D = 0.077, p = 0.026). The skew (0.56) and kurtosis values (-0.047) for the distribution of scores were also not considered problematic.

A Pearson's test found that the correlation between scores on the ZAS and participant's ages was non-significant (r = -0.06, p = 0.23).

Sex	Diagnosis	Mean	SD	N
Male	Control	34.27	8.94	40
	Autism	41.12	11.04	99
Female	Control	39.20	10.46	64
	Autism	43.97	9.46	159

Table 10.5 Participant descriptives for the Zung Self-rating Anxiety Scale (ZAS) within the sex-balanced sample. Mean, standard deviation (SD) and sample size (N) are shown for all subgroups after stratifying based on sex and diagnosis.

A 2-way ANOVA was conducted with IUS as the outcome measure and diagnostic status and sex as the 2 independent variable. Type III Sum of Squares was used as detailed in chapter 8. There was a significant effect of diagnostic status which remained significant after correcting for multiple testing ($F(1, 358) = 23.19$, $p < 0.001$, $\eta^2 = 0.059$). There was a significant effect of sex ($F(1, 358) = 10.40$, $p = 0.001$, $\eta^2 = 0.026$) but the interaction between diagnostic status and sex was non-significant ($F(1, 358) = 0.745$, $p > 0.3$, $\eta^2 = 0.002$, see table 10.6).

Cases	Sum of Squares	df	Mean Square	F	p	η^2
Sex	1060.38	1	1060.38	10.397	0.001	0.026
Diagnosis	2364.81	1	2364.81	23.186	< .001	0.059
Sex * Diagnosis	75.94	1	75.94	0.745	0.389	0.002
Residual	36513.72	358	101.99			

Table 10.6 Results from the 2-way ANOVA run on within the sex-balanced sample. Scores on the Zung Self-rating Anxiety Scale (ZAS) were used as the outcome measure and diagnostic status and sex were used as the 2 independent variable.

Glasgow Sensory Questionnaire

Within the sex-balanced sample, 362 participants completed the GSQ. The average score across all participants was 66.86 (SD = 27.04). Participant descriptives for scores on the GSQ are shown in table 10.7.

The K-S test was non-significant (D = 0.028, $p > 0.3$). The skew (0.14) and kurtosis values (-0.35) for the distribution of scores were also not considered problematic.

A Pearson's test found that the correlation between scores on the GSQ and participant's ages was non-significant (r = -0.05, $p > 0.3$).

Sex	Diagnosis	Mean	SD	N
Male	Control	44.02	23.05	40
	Autism	73.25	24.99	99
Female	Control	45.5	20.72	64
	Autism	77.23	22.84	159

Table 10.7 Participant descriptives for the Glasgow Sensory Questionnaire (GSQ) within the sex-balanced sample. Mean, standard deviation (SD) and sample size (N) are shown for all subgroups after stratifying based on sex and diagnosis.

A 2-way ANOVA was conducted with GSQ as the outcome measure and diagnostic status and sex as the 2 independent variable. Type III Sum of Squares was used as detailed in chapter 8. There was a significant effect of diagnostic status which remained significant after correcting for multiple testing ($F(1, 358) = 120.55$, $p < 0.001$, $\eta^2 = 0.251$). There was neither a significant effect of sex ($F(1, 358) = 0.963$, $p > 0.3$, $\eta^2 = 0.002$) or significant interaction between diagnostic status and sex ($F(1, 358) = 0.203$, $p > 0.3$, $\eta^2 = 0.000$, see table 10.8).

Cases	Sum of Squares	df	Mean Square	F	p	η^2
Sex	520.7	1	520.7	0.963	0.327	0.002
Diagnosis	65164.6	1	65164.6	120.551	$< .001$	0.251
Sex * Diagnosis	109.5	1	109.5	0.203	0.653	0.000
Residual	193519.5	358	540.6			

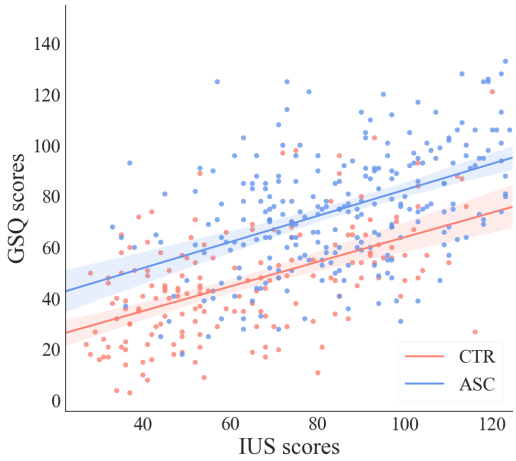
Table 10.8 Results from the 2-way ANOVA run on within the sex-balanced sample. Scores on the Glasgow Sensory Questionnaire (GSQ) were used as the outcome measure and diagnostic status and sex were used as the 2 independent variable.

Summary of sex-balanced sample

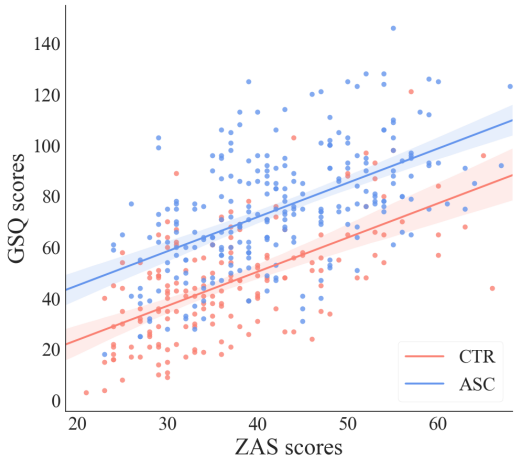
The characteristics of the 4 measures detailed above were very similar within the sex-balanced sample as they were within the full sample. Overall group means were similar for all measures. Subgroup means were also similar after stratifying the sample based on sex and diagnosis. There were no issues with normality across any of the measures within the sex-balanced sample. Effects of age for all measures were similar to those reported in the full sample. Effect sizes for the group differences were also similar across all measures. The largest difference in effect size between the full and sex-balanced samples occurred within the ZAS, where the effect of diagnosis decreased (Full sample: $\eta^2 = 0.081$, sex-balanced sample: $\eta^2 = 0.059$). The only measure that showed a significant effect of sex was the ZAS. This is in line with the findings from the full sample, however the effect of sex increased slightly (Full sample: $\eta^2 = 0.016$, sex-balanced sample: $\eta^2 = 0.026$). As the ratio of males and females were now balanced across the two diagnostic groups in the new sample, this effect of sex was not considered problematic as the interaction between the diagnosis and sex terms was non-significant. All mediation analyses presented in this chapter were carried out initially in the full-sample and then repeated in the sex-balanced sample.

10.3.2 Covariance between clinical questionnaire measures

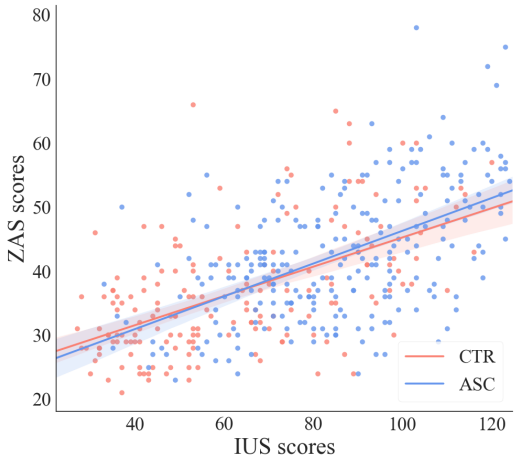
Correlations were plotted for all combinations of pairs within the 3 measures of interest: GSQ, IUS and the ZAS (see figure 10.2). While the direction of correlation for the two interactions involving sensory sensitivities both appear to be in a different direction to the results presented by Neil et al. (2016), this is due to the different measures used in their study and the present analysis. Neil et al. (2016) used the Short Sensory Profile, in which *higher* scores indicate *lower* levels of symptoms, whereas the GSQ was used in this study, where *higher* scores indicate *higher* levels of symptoms.



(a) IUS and GSQ scores



(b) ZAS and GSQ scores



(c) IUS and ZAS scores

Fig. 10.2 Scatterplots showing the relationships between (a) Intolerance of Uncertainty Scale (IUS) and Glasgow Sensory Questionnaire (GSQ) scores, (b) Zung Self-rating Anxiety Scale (ZAS) and GSQ scores and (c) IUS and ZAS scores. Individual points and lines of best fit are shown for autistic and non-autistic individuals. Higher scores on all 3 measures indicate greater levels of symptoms.

IUS and GSQ

IUS scores were significantly correlated with GSQ scores in the overall sample ($r = 0.606,\ p < 0.001$), as well as in the autism group ($r = 0.453,\ p < 0.001$) and the control group ($r = 0.567,\ p < 0.001$). A Fisher transform was used to assess whether the strength of this correlation significantly differed between the two groups (Fisher, 1915). Two-tailed tests were used for as there were no *a priori* hypotheses regarding the relative strength of correlations between the two groups. The difference in correlations between the autism group and the controls was non-significant ($Z = 1.4,\ p = 0.162$ two-tailed test).

ZAS and GSQ

ZAS scores were significantly correlated with GSQ scores in the overall sample ($r = 0.617,\ p < 0.001$), as well as in the autism group ($r = 0.538,\ p < 0.001$) and the control group ($r = 0.598,\ p < 0.001$). The difference in correlations between the autism group and the controls was non-significant ($Z = 0.81,\ p > 0.3$ two-tailed test).

IUS and ZAS

IUS scores were significantly correlated with ZAS scores in the overall sample ($r = 0.588,\ p < 0.001$), as well as in the autism group ($r = 0.540,\ p < 0.001$) and the control group ($r = 0.539,\ p < 0.001$). The difference in correlations between the autism group and the controls was non-significant ($Z = -0.01,\ p > 0.3$ two-tailed test).

10.3.3 Intolerance of uncertainty as a mediator for the relationship between autism and anxiety

Both Neil et al. (2016) and Boulter et al. (2014) reported that intolerance of uncertainty mediated the relationship between autism diagnosis and anxiety in children. I aimed to test whether the same relationship existed in an adult population by carrying out a similar mediation analysis in the dataset. To match the group based analysis of Neil et al. (2016) and Boulter et al. (2014) the analysis was initially carried out using autism diagnosis, entered as a binary variable, as the predictor variable. Then an additional analysis was carried out using AQ scores as the predictor variable, to match the trait-based approach of Maisel et al. (2016).

Autism Diagnosis

The first analysis used diagnosis as the independent variable, ZAS scores as the dependent variable and IUS scores as the mediating variable. The model suggested that an autism

diagnosis was associated with a 22.96 ($S.E. = 2.06$) increase in scores on the IUS. Adjusting for autism diagnosis, every 1 point increase in IUS scores was associated with an increase of 0.23 ($S.E. = 0.02$) on the ZAS.

The direct effect (c) of diagnosis on ZAS scores ($b = 6.18,\ S.E. = 0.88,\ p < 0.001$) was significant. The direct effect (c') of diagnosis on ZAS scores when controlling for IUS scores ($b = 0.8,\ S.E. = 0.82,\ p = 0.33$) was non-significant suggesting there was no sufficient evidence that autism diagnosis was associated with ZAS scores independent of its association with performance on the IUS. The estimated indirect effect (ab) of diagnosis on ZAS scores through IUS scores was ($b = 5.38,\ S.E. = 0.66,\ 95\%\ BCa\ CI[4.15,\ 6.73],\ p < 0.001$).

This suggests that diagnostic status was found to be associated with an increase in ZAS scores indirectly through increases in IUS scores. Specifically, for every 22.96 increase in IUS score driven by diagnostic status, there was a 5.38 increase in ZAS scores (mediation model shown in figure 10.3). The full model explained 36% of the variance in performance on the ZAS.

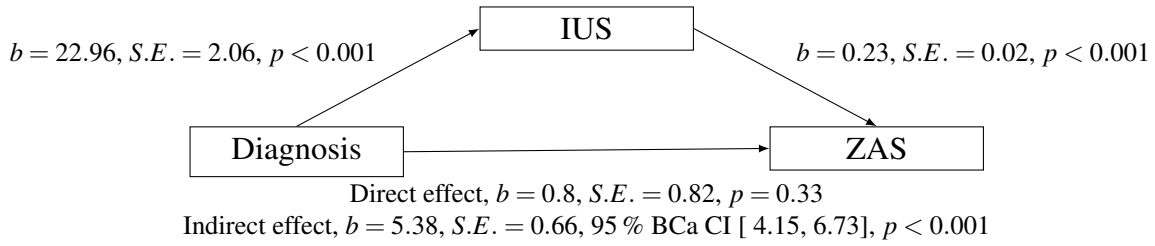


Fig. 10.3 The model of diagnostic status as a predictor of anxiety (ZAS scores), mediated by intolerance of uncertainty (IUS scores) for all participants. A BCa bootstrapped confidence interval based on 1000 samples was used to estimate the CI for the indirect effect.

The same analysis was also run in the sex-balanced sample, to check that the result wasn't due to potential underlying sex effects. The direct effect (c) of diagnosis on ZAS scores ($b = 5.57,\ S.E. = 1.19,\ p < 0.001$) remained significant and the direct effect (c') of diagnosis on ZAS scores after controlling for performance on the IUS ($b = -0.68,\ S.E. = 1.08,\ p = 0.53$) remained non-significant. The indirect effect ($b = 6.26,\ S.E. = 0.88,\ 95\%\ BCa\ CI[4.59,\ 8.14],\ p < 0.001$) and variance explained by the model ($R_2 = 0.37$) also did not change significantly in the new sample.

Autistic traits

A similar analysis was then run using AQ scores as opposed to diagnostic status as the independent variable, ZAS scores as the dependent variable and IUS scores as the mediating variable. The analysis suggested that a 1-point rise in AQ scores was associated with a 0.5 ($S.E. = 0.1$) increase in scores on the IUS. Adjusting for autism diagnosis, every 1 point increase in IUS score was associated with an increase of 0.25 ($S.E. = 0.02$) on the ZAS.

The direct effect (c) of AQ scores on ZAS scores ($b = 0.12,\ S.E. = 0.04,\ p = 0.0028$) was significant. The direct effect (c') of AQ scores on ZAS scores after controlling for peformance on the IUS ($b = 0,\ S.E. = 0.03,\ p = 0.97$) was non-significant suggesting there was no sufficient evidence that AQ scores were associated with ZAS scores independent of the association with IUS scores. The estimated indirect effect (ab) of AQ scores on anxiety through IUS was ($b = 0.13,\ S.E. = 0.03,\ 95\%\ BCa\ CI[0.07,\ 0.18],\ p < 0.001$).

This suggests that, similarly to diagnostic status, AQ scores were associated with an increase in ZAS scores indirectly through increases in IUS scores. Specifically, for every 0.5 increase in IUS score driven by AQ scores, there was a 0.12 increase in ZAS score (the mediation model is shown in figure 10.4). Similarly to the previous model, 37% of the variance in anxiety scores was explained by the AQ score based model. Again, the same analysis was also run in the sex-balanced sample and the results held.

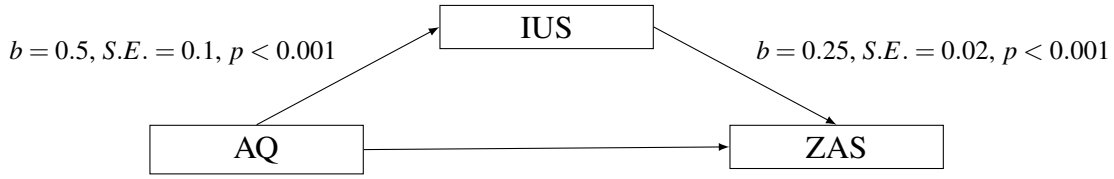


Fig. 10.4 The model of autistic traits (AQ scores) as a predictor of anxiety (ZAS scores), mediated by intolerance of uncertainty (IUS scores) for all participants. A BCa bootstrapped confidence interval based on 1000 samples was used to estimate the CI for the indirect effect.

Mediating role of diagnosis on the association of autistic traits with intolerance of uncertainty and anxiety

The association of the AQ with the IUS and the ZAS was examined to assess whether there was a true effect of AQ scores on these two measures or whether the previously reported effects were being driven by diagnostic status. Spearman's correlations were calculated for

AQ scores with IUS and ZAS scores in the overall sample, as well as in both autism- and control-only samples. For these analyses, the sex-balanced sample was used to avoid any potential confounds of sex. These correlations are shown in figure 10.5 .

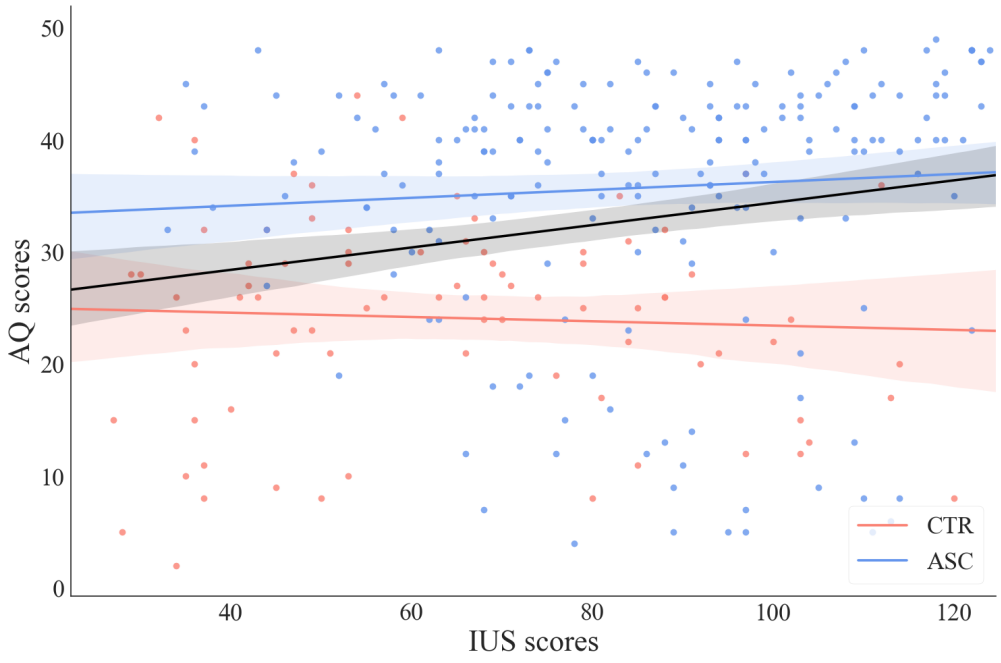
AQ scores were significantly correlated with IUS in the overall sample ($r = 0.247,\ p < 0.001$). This correlation remained significant but was reduced in size within the autism group ($r = 0.173,\ p = 0.014$) and was non-significant in the control group ($r = -0.056,\ p > 0.3$). Fisher transforms were used to assess whether the relationship between IUS and AQ significantly differed across the 3 samples (Fisher, 1915). One-tailed tests were used for comparing the individual group samples with the overall sample, as it was predicted that correlations in the individual group samples would be weaker. The Fisher transforms found the difference in correlations between the overall and autism samples ($Z = 0.82,\ p = 0.206$ one-tailed test) was non-significant, while the difference in correlations between the overall and control samples ($Z = 2.39,\ p = 0.008$ one-tailed test) was significant.

AQ scores were significantly correlated with ZAS scores in the overall sample, as previously reported ($r = 0.16,\ p = 0.007$). This correlation remained significant but was reduced in size within the autism group ($r = 0.145,\ p = 0.041$) and was non-significant in the control group ($r = -0.067,\ p = 0.55$). In a similar trend to the IUS results, the Fisher transforms found the difference in correlations between the overall and autism samples ($Z = 0.17,\ p > 0.3$ one-tailed test) was non-significant, while the difference in correlations between the overall and control samples ($Z = 1.78,\ p = 0.037$ one-tailed test) was significant.

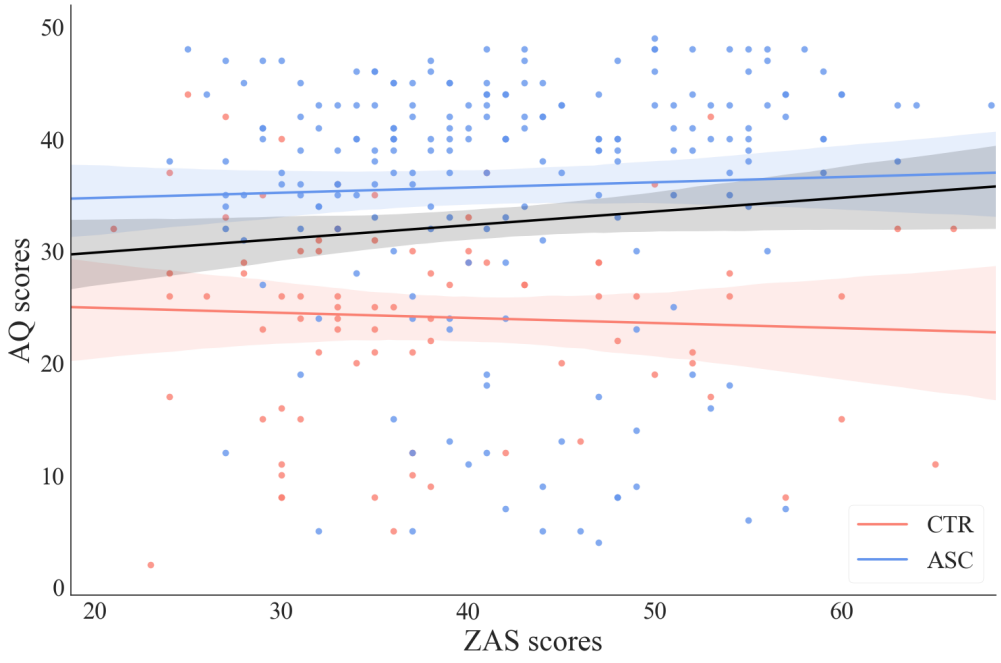
To assess whether the effects of AQ scores on IUS and ZAS scores were driven by diagnosis, further mediation analyses were run with AQ scores as the independent variable, IUS or ZAS scores as the dependent variable and diagnostic status as the mediator. When IUS scores were used as the dependent variable, the results indicated that that a 1-point rise in AQ scores was associated with a 2% increase in the likelihood that an individual has a diagnosis of autism. Adjusting for AQ scores, the effect of having a diagnosis was associated with an increase of 23.82 ($S.E. = 2.99$) in IUS scores.

The direct effect (c) of AQ on IUS ($b = 0.46,\ S.E. = 0.11,\ p < 0.001$) was significant. The direct effect (c') of AQ on IUS after controlling for diagnostic status ($b = 0.06,\ S.E. = 0.11,\ p > 0.3$) was non-significant suggesting there was no sufficient evidence that AQ scores were associated with IUS scores independent of the association with diagnostic status. The estimated indirect effect (ab) of AQ scores on IUS scores through diagnostic status was ($b = 0.4,\ S.E. = 0.07,\ 95\%\ BCa\ CI[0.27,\ 0.55],\ p < 0.001$). The mediation model is shown in figure 10.6.

When ZAS scores were used as the dependent variable, the results indicated that the effect of having a diagnosis, after adjusting for AQ scores, was associated with an increase



(a)



(b)

Fig. 10.5 Scatterplots showing the relationships between (a) Intolerance of Uncertainty Scale (IUS) and Autism Spectrum Quotient (AQ) scores and (b) and Zung Self-rating Anxiety Scale (ZAS) and AQ scores. Individual points and lines of best fit are shown for autistic and non-autistic individuals separately. The black lines show the line of best fit for all participants (both autistic and non-autistic individuals).

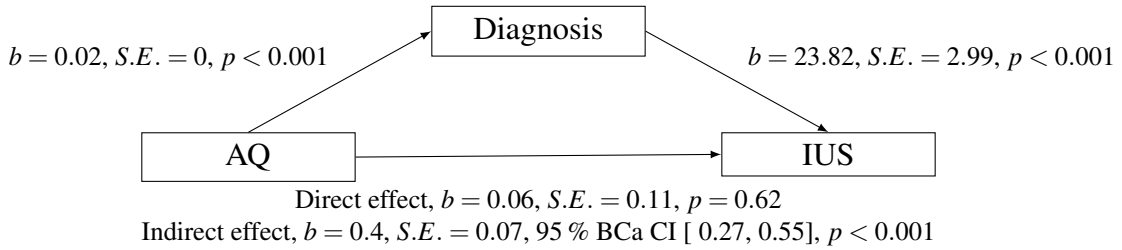


Fig. 10.6 The model of autistics traits (AQ scores) as a predictor of intolerance of uncertainty (IUS scores), mediated by diagnostic status within the sex-balanced sample. A BCa bootstrapped confidence interval based on 1000 samples was used to estimate the CI for the indirect effect.

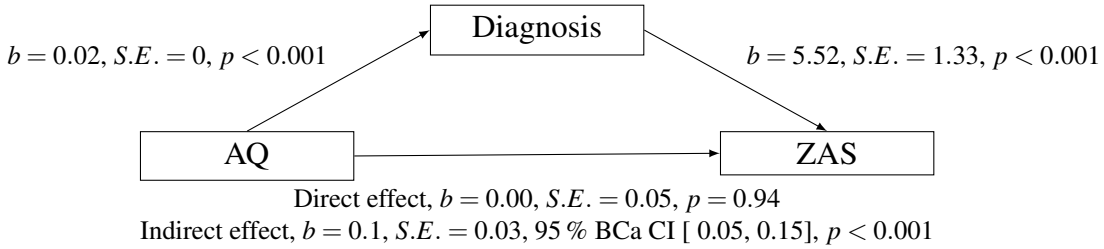


Fig. 10.7 The model of diagnostic status as a predictor of anxiety (ZAS scores), mediated by intolerance of uncertainty (IUS scores) for all participants. A BCa bootstrapped confidence interval based on 1000 samples was used to estimate the CI for the indirect effect.

of 5.52 ($S.E. = 1.33$) on ZAS scores. The direct effect (c) of AQ on ZAS ($b = 0.1,\ S.E. = 0.05,\ p < 0.037$) was significant. The direct effect (c') of AQ on IUS after controlling for diagnostic status ($b = 0,\ S.E. = 0.05,\ p = 0.94$) was non-significant suggesting that AQ scores were not associated with ZAS scores independently of the association with diagnostic status. The estimated indirect effect (ab) of AQ scores on IUS through diagnostic status was ($b = 0.1,\ S.E. = 0.03,\ 95\%\ BCa\ CI[0.05,\ 0.15],\ p < 0.001$). The mediation model is shown in figure 10.7.

These results suggest that AQ scores had an indirect effect on both IUS and ZAS scores through diagnostic status. This seems to be driven by the fact that autistic traits, as measured by the AQ, are elevated in individuals with autism (as reported in chapter 8). This suggests that intolerance of uncertainty and anxiety occur as distinct features in autism, independently of autistic traits as measured by the AQ.

10.3.4 Intolerance of uncertainty as a mediator for the relationship between autism and sensory issues

In addition to mediating the relationship between diagnostic status and anxiety, Neil et al. (2016) also reported that IUS mediated the association between diagnostic status and sensory issues in autistic children. Mediation analysis was again used to see whether this relationship existed in an adult population. Again, this analysis was carried out twice using each of autism diagnosis and AQ scores as the predictor variable.

Autism diagnosis

A mediation analysis was conducted using diagnostic status as the independent variable, GSQ scores as the dependent variable and IUS scores as the mediating variable. The mediation model suggested that every 1 point increase in IUS scores was associated with an increase of 0.5 ($S.E. = 0.04$) in GSQ scores.

Both the direct effect (c) of diagnostic status on GSQ scores ($b = 29.55$, $S.E. = 2.24$, $p < 0.001$) and the direct effect (c') of after controlling for performance on the IUS ($b = 17.78$, $S.E. = 2.17$, $p < 0.001$) were significant, suggesting that a full mediation effect was not present in the model. However, the estimated indirect effect (ab) of diagnosis on GSQ scores through IUS scores was still significant, indicating that a partial mediation effect was present ($b = 11.76$, $S.E. = 1.56$, 95% *BCa CI*$[8.73, 14.82]$, $p < 0.001$).

This suggests that the association between diagnostic status and GSQ scores was partially due to an indirect effect through IUS scores (see figure 10.8). The full model including both diagnostic status and IUS explained a large proportion of the variance (47%) in GSQ scores. Rerunning the analysis in the sex-balanced sample did not change the result.

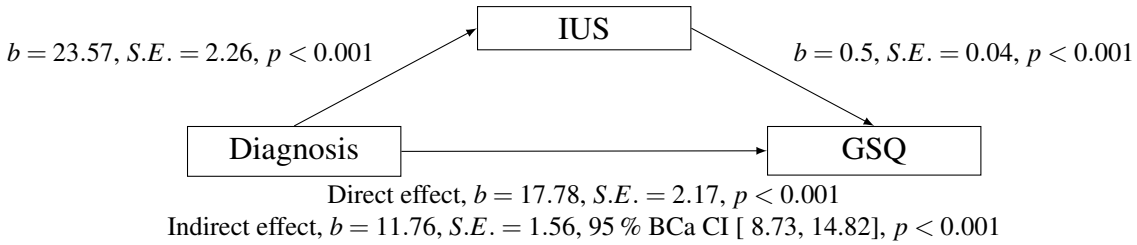


Fig. 10.8 The model of diagnostic status as a predictor of sensory issues (GSQ scores), mediated by intolerance of uncertainty (IUS scores) in all participants. A BCa bootstrapped confidence interval based on 1000 samples was used to estimate the CI for the indirect effect.

Autistic traits

A mediation analysis was run again using AQ instead of diagnostic status as the independent variable. Similar to the previous analysis, the results suggested that a full mediation effect was not present as both the direct effect (c) of AQ on GSQ ($b = 0.64,\ S.E. = 0.1,\ p < 0.001$) and the direct effect (c') after controlling for IUS ($b = 0.32,\ S.E. = 0.1,\ p < 0.001$) were significant. Both the confidence interval of the estimated indirect effect (ab) and the significant suggested a true indirect effect was present ($b = 0.29,\ S.E. = 0.09,\ 95\%\ BCa\ CI[0.12,\ 0.47],\ p < 0.0001$). These results also indicated that only a partial mediation effect was present (see figure 10.9). The model using AQ explained a slightly smaller proportion of the variance (41%) in GSQ scores than the model using diagnostic status did. Again, similar results were found after rerunning the analysis in the sex-balanced sample.

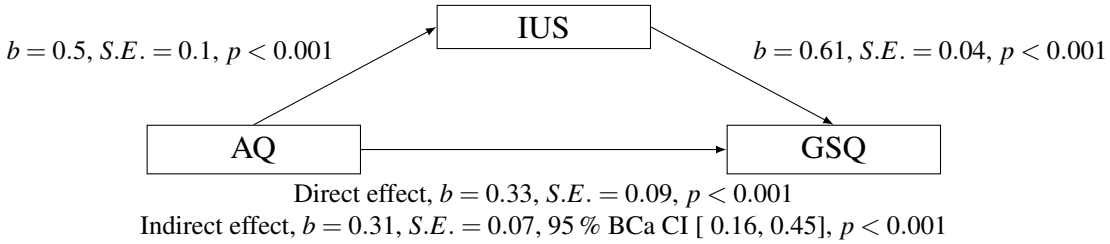


Fig. 10.9 The model of autistic traits as a predictor of sensory issues (GSQ scores), mediated by intolerance of uncertainty (IUS scores) in all participants. A BCa bootstrapped confidence interval based on 1000 samples was used to estimate the CI for the indirect effect.

Mediating role of diagnosis on the association of autistic traits with sensory issues

As was done with the IUS and ZAS, the relationship between AQ and GSQ scores was examined to assess whether there was a direct effect of AQ scores on GSQ scores or whether this effect occurred indirectly through diagnostic status. Spearman's correlations were calculated for AQ and GSQ scores in the overall sample, as well as in both autism and control only samples. Again, the sex-balanced sample was used to avoid any potential confounds of sex.

AQ scores were significantly correlated with GSQ scores in the overall sample ($r = 0.368,\ p < 0.001$). This correlation remained significant but was reduced in size within the autism group ($r = 0.275,\ p < 0.001$) and was non-significant in the control group ($r = -0.033,\ p = 0.77$). Scatterplots showing the 3 correlations are shown in figure 10.10.

Fisher transforms were used to assess whether the relationship between AQ and GSQ scores significantly differed across the 3 samples (Fisher, 1915). Again, one-tailed tests were used for comparing the individual group samples with the overall sample. The Fisher transforms found the difference in correlations between the overall and autism samples ($Z = 1.11,\ p = 0.133$ one-tailed test) was non-significant, while the difference in correlations between the overall and control samples ($Z = 3.25,\ p < 0.001$ one-tailed test) was significant.

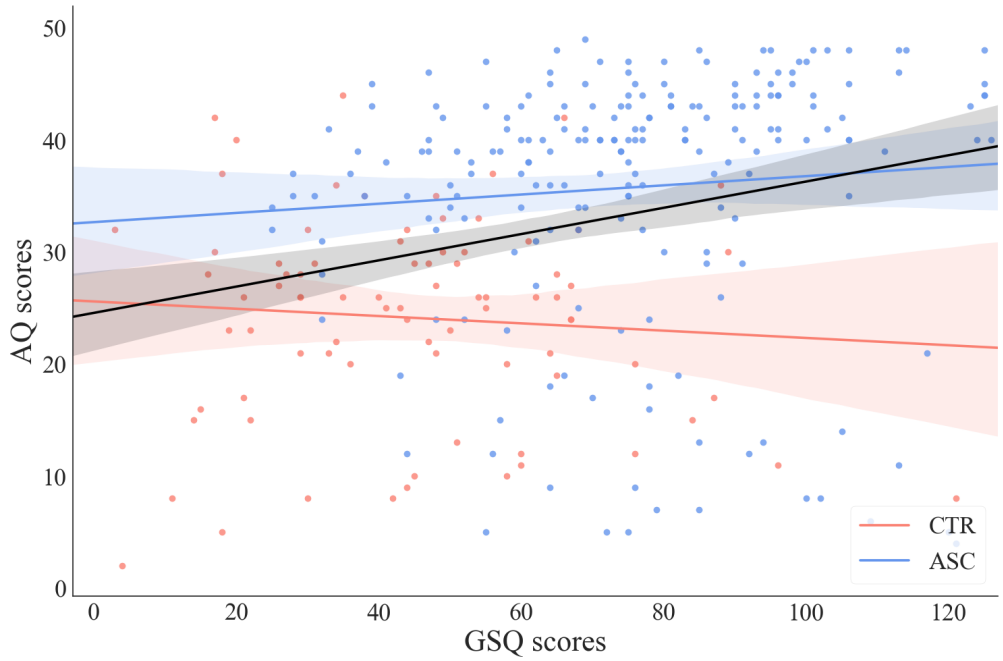


Fig. 10.10 Scatterplot showing the relationships between Glasgow Sensory Questionnaire (GSQ) scores and Autism Spectrum Quotient (AQ) scores. Individual points and lines of best fit are shown for autistic and non-autistic individuals separately. The black lines show the line of best fit for all participants (both autistic and non-autistic individuals).

To assess whether the effect of AQ scores on GSQ score was driven by diagnosis, an additional mediation analysis was run with AQ scores as the independent variable, GSQ scores as the dependent variable and diagnostic status as the mediator. Adjusting for AQ scores, the effect of having a diagnosis was associated with an increase of 29.46 ($S.E. = 3.01$) in GSQ scores. The direct effect (c) of AQ on IUS ($b = 0.61,\ S.E. = 0.12,\ p < 0.001$) was significant. The direct effect (c') of AQ on IUS after controlling for diagnostic status ($b = 0.11,\ S.E. = 0.11,\ p = 0.33$) was non-significant suggesting a lack of sufficient evidence that AQ scores were directly associated with IUS scores independent of the association with diagnostic status. The mediation model is shown in figure 10.11. The estimated indirect effect (ab) of AQ scores on IUS scores through diagnostic status was ($b = 0.5,\ S.E. = 0.07,\ 95\%\ BCa\ CI[0.35,\ 0.64],\ p < 0.001$).

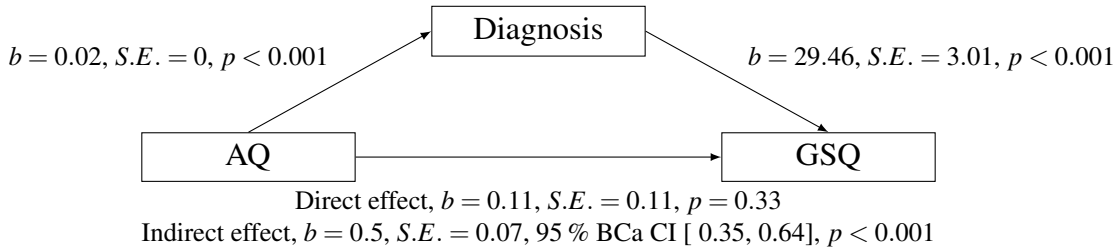


Fig. 10.11 The model of autistics traits (AQ scores) as a predictor of sensory issues (GSQ scores), mediated by diagnostic status within the sex-balanced sample. A BCa bootstrapped confidence interval based on 1000 samples was used to estimate the CI for the indirect effect.

10.3.5 Anxiety as a mediator for the relationship between intolerance of uncertainty and sensory issues

Neil et al. (2016) also reported that the relationship between intolerance of uncertainty and sensory issues was partially mediated by anxiety. Again, a similar analysis was carried out to see whether this relationship also existed in an adult population. The mediating effect was assessed separately in control and autism participants taken from the sex-balanced sample.

Autism sample

Scores on the IUS were used as the independent variable in a mediation analysis with GSQ scores as the dependent variable and ZAS scores as the mediating variable. Both the direct effect (c) of IUS on GSQ ($b = 0.51,\ S.E. = 0.06,\ p < 0.001$) and the direct effect (c') of after controlling for ZAS ($b = 0.25,\ S.E. = 0.06,\ p < 0.001$) were significant. The estimated indirect effect (ab) was significant suggesting a partial mediation effect was present in the autism sample ($b = 0.26,\ S.E. = 0.04,\ 95\%\ BCa\ CI[0.18,\ 0.34],\ p < 0.001$). The mediation model is shown in figure 10.12. This suggests that the association between diagnostic status and GSQ scores was partially due to an indirect effect through ZAS scores. The full model explained 37% of the variance in GSQ scores.

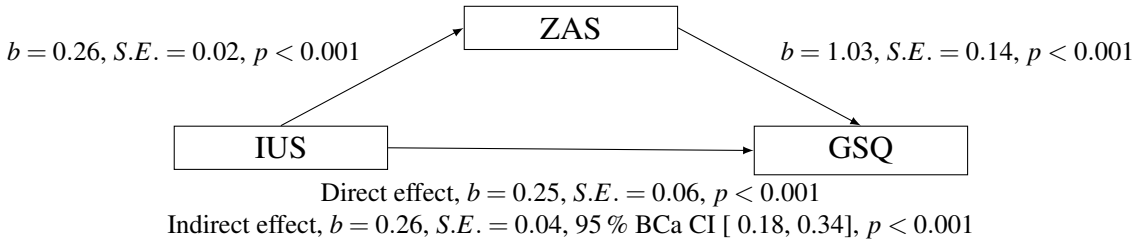


Fig. 10.12 The model of intolerance of uncertainty (IUS scores) as a predictor of sensory issues (GSQ scores), mediated by anxiety (ZAS scores) in autistic participants. A BCa bootstrapped confidence interval based on 1000 samples was used to estimate the CI for the indirect effect.

Control sample

Again, scores on the IUS were used as the independent variable in a mediation analysis with GSQ scores as the dependent variable and ZAS as the mediating variable. The direct effect (c) of IUS scores on GSQ scores ($b = 0.53,\ S.E. = 0.07,\ p < 0.001$) and the direct effect (c') of after controlling for ZAS scores ($b = 0.32,\ S.E. = 0.08,\ p < 0.001$) were both significant. The estimated indirect effect (ab) was significant, indicating that a partial mediation effect was also present in the control sample ($b = 0.21,\ S.E. = 0.06,\ 95\%\ BCa\ CI[0.12,\ 0.33],\ p < 0.001$). The model is shown in figure 10.13. This suggests that the association between IUS scores and GSQ scores was partially due to an indirect effect through ZAS scores. The full model explained 46% of the variance in GSQ scores.

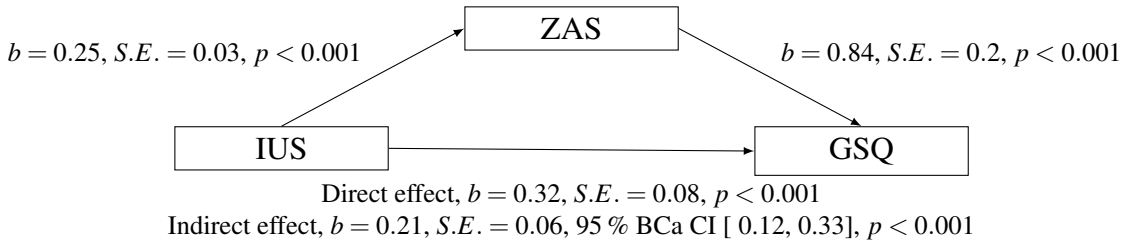


Fig. 10.13 The model of intolerance of uncertainty (IUS scores) as a predictor of sensory issues (GSQ scores), mediated by anxiety (ZAS scores) in control participants. A BCa bootstrapped confidence interval based on 1000 samples was used to estimate the CI for the indirect effect.

10.4 Discussion

In this chapter, I was able to extend previous research by showing that relationships between intolerance of uncertainty, anxiety and sensory issues, which had previously been reported in child (Neil et al., 2016) and adolescent populations (Boulter et al., 2014), were also present in an adult population.

The results reported here showed that intolerance of uncertainty fully mediated the association between autism and elevated levels of anxiety. This has extended the findings of Neil et al. (2016) to show that this mediating effect is also present in an adult population. While a similar analysis had been carried out in an adult population by Maisel et al. (2016), those findings were reported only the level of autistic traits and not for diagnostic status. The analyses presented here found a mediating role of intolerance of uncertainty on the association of both diagnostic status and autistic traits with anxiety. There was a full mediating effect of intolerance of uncertainty within the trait based analysis, which deviates slightly from the results of Maisel et al. (2016) as they reported a partial mediation effect.

Interestingly, an additional analysis revealed that autism diagnosis itself played a mediating role in the relationship between autistic traits and intolerance of uncertainty as well as the relationship between autistic traits and anxiety. This suggests that the correlation between autistic traits and the two other measures reported in the present sample are driven primarily by the presence of autism rather than variation in presentation of autistic traits. This is a novel finding and supports the case that uncertainty and anxiety are distinct features in autism and do not occur simply by association due to elevated levels of autistic traits in the autistic population.

I was also able to find a partial mediation effect of intolerance of uncertainty on the relationship between diagnostic status and sensory issues in the present sample. This is in line with the findings previously reported in children (Neil et al., 2016). This relationship was also found using autistic traits instead of diagnostic status. However, further analysis revealed that diagnostic status also mediated the association between autistic traits and sensory issues which suggests that sensory issues are a unique aspect of autism and not solely driven by their association with autistic traits.

Finally, I reported a partial mediation effect of anxiety on the relationship between diagnostic status and sensory issues in the present sample. This is again in line with the findings previously reported in children (Neil et al., 2016; Wigham et al., 2015), showing that these findings extend to an adult population. The results presented here did differ slightly from those previously reported, as there was a large difference in the strength of correlation between intolerance of uncertainty and sensory issues in the autism ($r = -0.67$) and control groups ($r = -0.38$) in children (Neil et al., 2016). Whereas, the results presented here

did found that the difference between this relationship in autistic ($r = 0.453,\ p < 0.001$) and non-autistic adults ($r = 0.567,\ p < 0.001$) was non-significant ($Z = 1.4,\ p = 0.162$ two-tailed test).

This may be due to a number of factors. Firstly, our recruitment was carried out online and so our autistic sample might have been biased towards containing a higher number of high-functioning individuals than the sample used by Neil et al. (2016). Equally, the fact that we used self-report measures whereas Neil et al. (2016) used parent-report measures may have led to some of the characteristics of the autism group being exaggerated in their child sample or under-reported in the present sample (Johnson et al., 2009). Finally, this could reflect a natural aspect of the development of this relationship from childhood to adulthood. A greater number of influencing factors as individuals develop throughout their lives could lead to the association between these two features weakening.

The original findings of Neil et al. (2016) were motivated by the hypo-priors account of perception in autism suggested by Pellicano and Burr (2012b). This theory hypothesises that difficulties in using prior experience during the processing of ambiguous sensory information could lead to an increased reliance on low level sensory information during perception which in turn could result in the atypical sensory perception often reported in autism. The fact that the results presented here showed that intolerance of uncertainty also had a direct effect on sensory sensitivities in adults with autism lends additional support to this theory in an adult population.

One limitation of this study is that, due to the results being collected online, IQ testing was not conducted on the participants in the study and so it was therefore impossible to ensure that the control and autism samples were matched on IQ. However, previous studies have shown that IQ is not correlated with any of the key measures in the present analyses: anxiety, sensory issues, intolerance of uncertainty or autistic traits (Baron-Cohen et al., 2001; Neil et al., 2016). Another limitation of the lack of an IQ measure in this study is that it means it's impossible to determine whether the participants within the autism sample would be regarded as high or low-functioning as this distinction is often regarded as key in autism research with regards to the applicability and generalisability of research findings. Another limitation is based on the recruitment approach in our control sample. Similar to the recruitment method of Maisel et al. (2016), control participants were screened for other conditions that might influence their performance on the measures administered in this study (such as anxiety disorders). As there is high prevalence of anxiety disorders in the autistic population (Gillott et al., 2001; Kim et al., 2000; White et al., 2009), taking a similar approach in the autism sample would have limited recruitment and also led to the autism sample not being representative of the true population. Future research could improve on

this by including controls with other conditions such as anxiety disorders and factoring these into the analyses.

Part V

Conclusion

Chapter 11

General discussion

The findings from each individual study have been discussed throughout the thesis within their respective chapters. The aim of this chapter is to bring these findings together, to assess how the overall thesis contributes to our understand of autism and to discuss how future research can build on the results presented here. The relevance of the findings of this thesis will be considered with regards to the suggestion that prior expectations have a reduced influence on perception in autistic individuals.

11.1 Behavioural results

This thesis presented results from three distinct behavioural paradigms that were each designed to assess different aspects of the ways in which prior expectations can influence perception. A summary of the results from these behavioural studies is given in table 11.1. The common underlying aim of these behavioural tasks was to assess whether there was evidence for a reduced influence of prior information in autism. While each of these behavioural tasks were developed to test specific hypotheses about the role of prior expectations during perception in autism, they all provided an opportunity to test the broad claim that prior expectations have a reduced influence in autistic individuals.

Across these behavioural studies, I found significantly reduced effects of prior expectations in the autism groups for two of the three tasks. The implications of these results, taken together, in relation to Bayesian accounts of autism will be discussed at the end of this chapter. Before doing so, the specific findings of each of these behavioural studies will be discussed in relation to the different hypotheses that each of them assessed.

Chapter	Aims	Main findings
Chapter 3	Test for group differences in basic search performance during an interrupted search task.	The autism group were found to be significantly slower in a non-search reaction time task. No differences were found in reaction times or error rates for basic performance in the search task.
Chapter 4	Test for effects of rapid resumption in autism and control groups and assess whether differences exist between the two groups in the extent of the effect.	Evidence for the effects of rapid resumption were found in both the control and the autism groups. This demonstrates that both groups were able to use information from previous exposures of the search display to facilitate search. The size of the rapid resumption effect was compared between the two groups and was found to be non-significant.
Chapter 5	Use a novel approach to verify the findings from chapter 4.	A Gaussian mixture model was successfully fit to the data and was used to requantify the rapid resumption effects. The results were in line with those from the previous chapter, providing additional evidence in support of intact use of prior information during visual search in autism.
Chapter 6	Assess whether autistic individuals update their prior expectations in a similar manner to non-autistic controls.	The autism group showed a significantly reduced effect of expectations in a serial reaction time task. There was also evidence to suggest that the extent to which the effect of expectations increased over time was reduced in autistic individuals relative to non-autistic controls. However, the autism group did not differ from controls in the extent to which they were affected by a reversal of the underlying statistical regularities in the task.
Chapter 7	Assess whether autistic individuals were able to learn and generalise statistical regularities at higher perceptual levels.	Following a serial presentation task in which participants were presented with a sequence containing structural information, the autism group showed a significantly reduced recall effect in a 2-choice forced alternative task. This effect was found when data was considered across all task conditions. No condition specific group differences were found.

Table 11.1 A number of different behavioural studies were carried out within this thesis to assess the extent to which autistic individuals were influenced by prior expectations. A summary of these different experiments and their results are presented here.

11.1.1 Influence of prior information on visual attention in autism

The first section of this thesis examined the effects of prior expectations on visual attention using an interrupted search task. The data from this task was presented across 3 separate chapters in order to comprehensively assess performance in the task. The first of these, chapter 3, considered overall search performance on the task to test whether performance differed between the two groups. This was important as autistic individuals have previously been reported to outperform non-autistic controls in visual search tasks (Joseph et al., 2009; O'riordan et al., 2001; Plaisted et al., 1998b). Chapter 4 then tested for the effects of rapid resumption in both autistic and non-autistic individuals, before using the method suggested by Lleras et al. (2011a) to assess whether autistic individuals differed from non-autistic controls in the extent to which they used prior information during the search task. The results found that autistic individuals showed evidence of the effects of rapid resumption and did not differ from non-autistic individuals in the extent of this effect.

The final chapter that considered data from the interrupted search task, chapter 5, introduced an additional modelling approach to verify the results from chapter 4. The results from this chapter supported the method suggested by Lleras et al. (2011a) and further supported the finding that autistic individuals used prior information to facilitate visual search in a similar manner to non-autistic controls. Overall, this set of studies provides strong evidence for one situation in which autistic individuals do not show a reduced influence of prior information. This is one of the first tasks to assess how autistic individuals use prior information during visual search and therefore it is difficult to draw any strong conclusions from this as a standalone study. Nonetheless, possible interpretations of the findings will be discussed as well as consideration of future extensions of this work.

The number of previous studies that have looked at the extent to which prior expectations influence spatial attention in autistic individuals is fairly limited. Research into the effects of perceptual load on attention in autism has found that autistic individuals show reduced levels of top-down attentional biases towards faces (Remington et al., 2012) and objects related to circumscribed interests (Parsons et al., 2017). These results suggest that there are cases in which autistic individuals do show differences in the extent to which their attention is affected by prior information. However, it is important to note that the attentional biases that occur in non-autistic individuals in the studies by Remington et al. (2012) and Parsons et al. (2017) are distractor effects. If it were the case that autistic individuals were able to modulate the influence of prior information depending on the situation, then it suggests that it may indeed be the case that the extraction of prior information is intact in autism but differences in the ascribed precision of sensory information drive the perceptual atypicalities associated with the condition (Brock, 2012; Lawson et al., 2014).

While the results presented here suggested that autistic individuals were influenced by prior expectations to a similar extent to the non-autistic controls, there is still a great deal of scope for further investigation in this area. The prior information presented to participants in the interrupted search task was direct information about the target and distractor elements from previous presentations of the search display. As the task gave participants direct access to the search display, there is very little ambiguity or uncertainty in the information presented to the participants except for the limitations induced by the short exposure period. Autistic children have previously been shown to take longer to infer underlying statistical rules in a foraging-style search task (Pellicano et al., 2011). It may well be that autistic adults would display different behaviour to controls when predictive information within a search task isn't directly accessible and has a higher level of uncertainty.

There are a number of other aspects of the area of spatial attention in which the influence of prior information should be considered in autism. Contextual cueing is another behavioural paradigm in which participants are given prior access to the search display, but the information is presented over a longer time span to the interrupted search task (Chun and Jiang, 1998; Chun, 2000). This would allow for potential differences in the duration of attentional expectations to be explored (Pollmann, 2018; Schlagbauer et al., 2018). The effects of indirect associative information could also be assessed, through tasks that use predictive cues to influence visual search (Droll et al., 2006). Further assessment of how autistic individuals use prior information in these different situations should be carried out to fully understand the relationship between prior expectations and spatial attention in autism.

11.1.2 Flexibility of prior expectations in autism

Chapter 6 set out to test whether autistic individuals showed a reduced ability to update their prior expectations relative to non-autistic controls. This study was motivated by the suggestions of Van de Cruys et al. (2014) who predicted that autistic individuals would experience difficulties in tasks in which they were required to update their expectations, such as the previously reported difficulties found in reinforcement learning tasks (D'Cruz et al., 2013; Miller et al., 2015; South et al., 2012). Van de Cruys et al. (2014) specifically suggest that prediction errors are given an overly high precision in autistic individuals and that this precision is not adaptable to the level of uncertainty in their environment. They argue that atypical weighting of prior information could lead to the process of updating expectations being affected in one of two ways, either resulting in autistic individuals switching too often or switching too little, and they argue that the former is more likely.

Across the entire serial reaction time task used in chapter 6, there was a reduced effect of expectation in the autism group and the results indicated that expectation effects for autistic

participants tended not to increase over the duration of each session to the same extent as non-autistic controls. However, the two groups did not significantly differ in the extent to which expectation effects varied between the first and second sessions. This indicates that there was a lack of evidence to suggest that, relative to controls, the autism group found it harder to update their expectations following a probabilistic reversal. The latter result seems to go against the predictions made by Van de Cruys et al. (2014) as they specifically highlighted results from reinforcement learning tasks that reported difficulties in autistic individuals following reversals of the predictive associations (D'Cruz et al., 2013; Miller et al., 2015; South et al., 2012).

Interestingly, Van de Cruys et al. (2017) also made specific claims about the difficulties that autistic individuals might experience when the associations they were required to learn were probabilistic and not deterministic, stating that:

> "Non-repeating, accidental variations in the input will receive disproportionately high weight, resulting in overfitting to these irrelevant differences: models will be shaped by putative regularities that will not generalize."

This prediction seems to be in line with the finding of an overall reduction in expectation effect within the autism group. The serial reaction time task presented here had an underlying structure that was probabilistic in nature due to the fact that awareness of given context would inform participants of the most likely outcome to follow but, importantly, still included some degree of uncertainty. Previous studies using deterministic serial reaction time tasks reported a lack of differences between autistic and non-autistic individuals. The fact that a difference was reported in the present study is possibly due to the fact that, as predicted by Van de Cruys et al. (2014), incidental variations to the regular statistical structure may be given disproportionately high weight. This interpretation would imply that autistic individuals might update their expectations during improbable trials whereas non-autistic individuals would treat such trials as irrelevant discrepancies. This increased weighting to improbable trials could lead to autistic individuals showing a reduced expectation effect, as was reported in the study.

11.1.3 Generalisation of expectations in autism

Chapter 7 was designed to assess whether autistic individuals were able to extract associative information at higher-levels of perception, through semantic or feature-based regularities. There have been suggestions that autistic individuals might develop overly specific priors which aren't generalisable to other contexts (Van de Cruys et al., 2014). Specifically, Van de Cruys et al. (2017) claim that high precision of sensory information would lead to

weaker high-level predictions at the expense of overfitted low-level ones. In relation to these heightened low-level predictions, they explain how this can lead to difficulties in processing more complex associations:

> "While this happens at the expense of detecting more abstract regularities, note that the basic capacity of forming predictions remains unaffected. Rather, encoding of noise hampers discovery of regularities when these are embedded in more complex, noisy inputs."

I assessed this hypothesis at two separate levels, firstly by assessing whether information presented at a categorical level could be extracted by autistic individuals and then by testing whether information that was learnt in a specific context could be generalised to other contexts. The results did not find significant group differences in either of these specific areas. However, there was an overall effect across the different task conditions that showed that autistic individuals were not able to identify familiar sequences to the same extent as the non-autistic controls.

While this is by no means a comprehensive assessment of the ability to generalise prior expectations, it does give one example of an instance in which autistic individuals were found to process statistical information at a high level. However, it is important to note that this lack of a significant difference could be due to a lack of power. The specific hypotheses were assessed by considering only participants who completed the individual conditions within the task. This reduced the sample sizes considerably and may have been a factor in the fact that a main effect of group was found but there were no differences in any of the specific task conditions. Further investigation in this area needs to be carried out before drawing any firm conclusions.

11.2 Psychometric results

In addition to the behavioural results, I also set out to understand how autistic individuals differed in their attitudes towards uncertainty. This was in order to understand how potential differences in the way predictive information is processed and utilised in autistic individuals might lead to differences in higher-level beliefs, attitudes and behaviours. The psychometric studies also aimed to explore the relationship between these attitudes towards uncertainty and clinical features commonly reported in autism, such as anxiety and sensory processing difficulties. A summary of these results reported across these chapters is given in table 11.2. The specific findings of each of the different psychometric studies will be discussed in turn before considering how these tie into Bayesian models of perception in autism.

Chapter	Aims	Main findings
Chapter 8	Conduct a number of descriptive analyses across a range of questionnaire measures.	Significant differences were found between autistic and non-autistic individuals for all 8 of the questionnaire measures included in the study. A significant effect of age was found on the Autism Spectrum Quotient (AQ) and Systemising Quotient (SQ), and a significant effect of sex was found on the Zung Self-rating Anxiety Scale (ZAS).
Chapter 9	Understand how 'intolerance of uncertainty' relates to a number of other psychometric measures.	A stepwise backward elimination approach was used to fit a linear model to scores on the Intolerance of Uncertainty Scale (IUS). The key predictors of IUS scores were diagnostic status, ZAS scores, Glasgow Sensory Questionnaire (GSQ) scores and scores on the Toronto Alexithymia Scale-II (TAS).
Chapter 10	To replicate the findings of Neil et al. (2016) in an adult sample.	Scores on the IUS were found to fully mediate the association between diagnostic status and scores on the ZAS. This relationship also held when diagnostic status was replaced with AQ scores, however diagnostic status itself was found to have a mediating role in the relationship between AQ scores and intolerance of uncertainty as well as the relationship between scores on the AQ and anxiety. There was also a partial mediation effect of IUS scores on the relationship between diagnostic status and GSQ scores.

Table 11.2 A large set of psychometric data was collected in this thesis from both autistic and non-autistic participants. This dataset was evaluated across 3 different studies to understand the role of intolerance of uncertainty in autism and how it relates to other features of the condition. A summary of these different analyses and their results are presented here.

11.2.1 Group differences

While primarily carried out as a precursor to the subsequent chapters, chapter 8 does provide a useful output in itself by assessing group differences in a large sample across a range of measures. Many of these group differences had previously been reported in the literature, with some of the measures being administered in large-scale studies such as data collected on the AQ from impressive samples of upwards of half a million participants (Greenberg et al., 2018; Ruzich et al., 2015). For measures such as the IUS, such large-scale studies have not been carried out and so the data presented in this thesis provide a useful resource for understanding these constructs in autistic individuals. The sample presented here is the largest to look at intolerance of uncertainty in the autistic population and provides strong evidence to suggest that this measure is sensitive to differences in the autistic phenotype.

While the results presented here are the first time a difference in scores on the Obsessive-Compulsive Inventory-Revised (OCI) have been reported in autism, this finding needs to be treated with some caution. In particular, this is due to the fact that scores on the OCI were highly correlated with other psychometric measures and therefore the difference reported in autistic individuals could be driven by the association of OCI scores with these other measures. A better understanding of these relationships could also be gained from conducting further research which includes measures of restricted and repetitive behaviours such as the Adult Repetitive Behaviours Questionnaire-2 (Barrett et al., 2015), as this may be a mediating factor in the increased scores on the OCI in autistic individuals (Joyce et al., 2017; Lidstone et al., 2014; Rodgers et al., 2012b; Wigham et al., 2015).

11.2.2 Exploring the construct of intolerance of uncertainty

This thesis also explored the nature of intolerance of uncertainty as a psychological construct, specifically by looking at how variation in other trait-based questionnaire measures predicted performance on the IUS. This was done using a stepwise backward elimination approach to fit a number of linear models to scores obtained on the IUS. Within these linear models, the measures that were consistently included as predictors were diagnostic status, the ZAS, the GSQ and the TAS.

Interestingly, the set of questionnaires that were specifically designed to tap into different aspects of the autism phenotype, the AQ, Empathy Quotient (EQ) and SQ, were not strong predictors of intolerance of uncertainty and did not survive elimination in any of the linear models presented. Nonetheless, diagnostic status was a strong predictor of scores on the IUS and was included in each of the models discussed. A more detailed examination of these relationships is required but the results seem to indicate that the AQ, EQ and SQ

do not significantly explain any further variance in intolerance of uncertainty in addition to overall diagnostic status. This is interesting as these measures are usually sensitive to variation in the non-autistic population (Constantino and Todd, 2003; Hoekstra et al., 2007; Wheelwright et al., 2006) and have been found to correlate with a number of behavioural and psychometric measures (Caldwell-Harris and Jordan, 2014; Jonason and Krause, 2013; Towbin et al., 2005).

It is particularly interesting that the SQ is not considered a strong predictor of intolerance of uncertainty as one key aspect of the SQ is the measurement of a drive towards regularity and order (Allison et al., 2015; Baron-Cohen et al., 2003; Ling et al., 2009). On first consideration, the two constructs appear to be tapping into a similar set of preferences for regularity and certainty. However, the results presented here suggest this may not be the case. Indeed, the IUS was specifically designed to measure anxiety surrounding uncertainty rather than just a preference towards certainty (Freeston et al., 1994). Whereas the SQ looks at preferences towards objects and environments with high levels of order and certainty. It is therefore quite plausible that an individual would have an interest in systems and regularity without having anxiety and fear towards uncertainty. This suggests that high scores on the SQ should not necessarily be expected to lead to higher scores on the IUS.

Unsurprisingly, anxiety was a strong predictor of intolerance of uncertainty. This was expected not only based on a large body of research that has found associations between the two constructs but also due to the fact that the IUS, by definition, is designed to measure the level of anxiety an individual feels towards uncertainty (Freeston et al., 1994). While sensory issues were included as a predictor in 2 of the models considered in chapter 9, scores on the GSQ were not included in the more conservative, simplified model. This is not to say that sensory issues are not associated with intolerance of uncertainty, as the two constructs have previously been linked in other studies (Neil et al., 2016; Wigham et al., 2015). The removal of sensory issues as a predictor is possibly due to the fact that it also has strong associations with the other predictors included in the model. It may be the case that sensory issues are primarily associated with intolerance of uncertainty through other constructs. This was explored within the mediation analysis in chapter 10 and will be discuss in more detail below. It is also worth noting that the exclusion of this term only occurred when the backwards elimination process was forced beyond its natural stopping state in order to achieve a more conservative model.

The relationship between scores the IUS and the TAS is slightly less intuitive than for the other predictor terms included in the exploratory models. I discussed possible reasons for this association in chapter 9, suggesting that it might be driven by disruption to brain regions, such as the insula cortex and anterior cingulate cortex, that account for both emotional monitoring

and processing uncertainty (Ide et al., 2013; Kano and Fukudo, 2013). Interestingly, the only interaction term included in any of the models occurred between diagnostic status and the TAS. If a disruption to common brain regions linked to these two different constructs was the underlying cause of this association, then it could also explain this interaction effect as the association might have been predominantly driven by the autism group where disruption of these regions has been suggested (Di Martino et al., 2009).

While the models presented here all explained over 50% of the variance in scores on the IUS, there was still a substantial amount of unexplained variance. The psychometric measures included in this thesis were not exhaustive and other constructs, such as depression (Cai et al., 2018), could also explain a significant proportion of the variation in individuals' intolerance of uncertainty. Other potential predictors of intolerance of uncertainty, as well as further consideration of the relationship between alexithymia and intolerance of uncertainty in autistic and non-autistic individuals, should be explored in future studies.

11.2.3 Mediating effects

Overall, the results from the analyses in an adult population closely matched the previously reported findings found in children (Neil et al., 2016). Scores on the IUS were found to play a mediating role in the elevated levels of anxiety and sensory issues found in autistic individuals. This suggests that the previously reported relationship between anxiety, sensory issues and intolerance of uncertainty in autism is not specific to children and that this association continues into adulthood. While the direction of causality and exact nature of these relationships is not clear from this analysis, some potential explanations for these associations were given in chapter 10 as well as in Neil et al. (2016).

The findings presented in this study are, similarly to Neil et al. (2016), in line with the original suggestions of Pellicano and Burr (2012b) who suggested that a reduced influence of prior information during perception would lead to situations where processing ambiguous sensory information would result in an increased weighting of sensory signals. Neil et al. (2016) suggested that intolerance of uncertainty might drive behaviours in autistic individuals to minimise unpredictable aspects of their environment. This could lead to a hypervigilant state and rumination about potential adverse outcomes, explaining the increased levels of anxiety often reported in autism.

However, it is also possible that sensory sensitivities themselves drive anxiety and intolerance of uncertainty. The idea that increased sensory precision leads to the relative attenuation of prior information has been put forward as a potential mechanism by which the perceptual atypicalities linked to autism could be explained within a Bayesian framework (Brock, 2012; Lawson et al., 2014). This model also gives a plausible explanation of the

results found in this study. It is also important to clarify that, while the results were found in the adult sample presented here were similar to those reported by Neil et al. (2016), it cannot be assumed that the exact same mechanisms drive these associations in the different populations. As suggested by Neil et al. (2016), experimental interventions could help to clarify the underlying nature of the potential causal or bidirectional relationships between these different constructs.

11.3 Bayesian accounts of autism

The main motivation for the questions approached in this thesis stemmed from the theories of Pellicano and Burr (2012b) and other similar accounts (Brock, 2012; Lawson et al., 2014; van Boxtel and Lu, 2013; Van de Cruys et al., 2014), who proposed that many of the features of autism may be understood in terms of variation in the extent to which prior expectations influence perception and behaviour. As discussed earlier in the thesis, these accounts do differ in the specific claims they make about the exact mechanisms by which these variations occurs. However, they all agree on the overall view that a reduced *influence* of prior information could explain the core aspects of autism. The extent to which the data collected in this thesis are consistent with this overall claim will be discussed here.

Of the three behavioural studies included in this thesis, two of the tasks found significantly reduced effects of prior expectations in autistic individuals. This provides two cases that appear to support the theory that autistic individuals are influenced by prior information to a lesser extent than non-autistic individuals. The results of the interrupted search task found that participants in the autism group used prior information to facilitate visual search in a similar manner to participants in the control group. This result appears to be in conflict with the results of the other two behavioural studies as well as the claims of an attenuated influence of prior information in autism. Conflicting results are commonplace in research, particularly when trying to detect modest effects, and can occur for various different reasons. When this occurs it is important to try to understand whether the conflicting results reported are driven by experimental noise, where sampling effects or lack of statistical power may lead to type II errors, or whether the methodological differences between the studies that conflict with each other actually reveal useful insights about the nature of the underlying processes they are assessing. The behavioural studies included here had sample sizes large enough to give 90% power of detecting large effect sizes but may have been underpowered to detect smaller sample sizes.

Conflicting results have been reported in the area of repetition suppression, with some studies reporting a reduced effect in autism (Ewbank et al., 2017) and others reporting

no differences between autistic and non-autistic individuals (Utzerath et al., 2018). While these results could be considered contradictory, there are notable methodological differences between the two studies. Ewbank et al. (2017) looked at an adult sample whereas Utzerath et al. (2018) recruited adolescents for their study. The stimuli also varied between the two studies, with Ewbank et al. (2017) using face stimuli and Utzerath et al. (2018) using non-social images. It may have been the case that the different results from these two studies were simply due to statistical factors, where a lack of power in the non-significant study may have led to a type II error or sampling factors in the significant study might have led to a type I error. However, it is also possible that neither type I nor type II errors occurred in either study and the difference in results was a true effect driven by aspects of the methodologies used in the two studies. In this instance, it may be the case that reduced repetition suppression in autism is specific to face stimuli or it may be that this effect is only present in adults.

In the behavioural results presented in this thesis, there were numerous differences between the interrupted search task and the two other tasks. The tasks in which differences were found between autistic and non-autistic individuals both looked at forms of sequential learning, whereas the interrupted search task looked at visual attention. Additionally, the timeframes over which prior information was presented and then subsequently utilised varied between the tasks. The information presented in the interrupted search task occurred very shortly (in the magnitude of milliseconds) before participants were required to use it, whereas there was a much longer latency between the encoding and recall of information in the two sequential learning tasks. Finally, only male participants were recruited for the interrupted search task but males and females were recruited for the other two tasks. These examples highlight some of the differences between the interrupted search task and the sequential learning tasks. One interpretation for the lack of a group difference in the interrupted search task is that the claims of a universal reduction of the influence of prior information in autistic individuals is an oversimplification of the mechanisms involved in autism.

Since the initial publication of the paper by Pellicano and Burr (2012b), there have been a number of experimental studies published that have tried to empirically test the claims that prior expectations have a reduced influence on perception in autistic individuals. Several of these studies were previously mentioned in the discussion sections within the thesis, particularly in chapter 5. The results from these different studies vary in whether or not they reported significant group differences, similar to the studies presented within this thesis. While several studies have reported results in line with the claims of Pellicano and Burr (2012b), there are still a number of studies that reported typical influences of prior expectations in autistic individuals. It is worth considering the conditions under which these studies tend to report a lack of group differences. For example, studies looking

at 'pre-existing' prior expectations (expectations that would have been acquired before the behavioural study) such as the 'light-from-above' prior (Croydon et al., 2017) or the expectation for direct gaze (Pell et al., 2016) have tended to report intact use prior information in autistic individuals. These expectations are regarded to be very stable and so it may be the case that group differences only emerge when expectations are acquired in more dynamic environments (Van de Cruys et al., 2013, 2014).

Both of the sequential learning tasks, in which group differences were found, required participants to learn about temporal contingencies between stimuli. Expectations of upcoming stimuli are a key part of perception and influence a number of different aspects of cognition (Kok et al., 2013, 2014, 2012; Melloni et al., 2011; Summerfield and Egner, 2009). The ability to update and change these expectations to adapt to changing environments is vital in order to optimise one's predictions about the world (Iglesias et al., 2013; Nassar et al., 2010; Philiastides et al., 2010). One concept that taps into this is the idea of perceived *volatility* of one's environment, the ability to infer the level of variability in the underlying statistical regularities over time. Lawson et al. (2017) presented data from a task in which participants were asked to respond to stimuli that were preceded by a predictive auditory cue. The strength of association between the predictive cue and the associated stimuli varied throughout the task and the level of volatility in the task, or the rate at which these changes to the underlying probabilities occurred, was also manipulated.

The results from this study found that autistic individuals tended to perceive the volatility of the task as higher than it really was (Lawson et al., 2017). While the main focus of their study was aimed at assessing how well autistic individuals could infer about the volatility of their environment, the authors also reported a reduced effect of expectations on reaction times in the autism group relative to controls. These findings also support the broad claims of a reduced influence of prior expectations in autism, as well as providing evidence specifically about higher level beliefs concerning volatility. This additional finding from Lawson et al. (2017), along with the findings from the sequential learning tasks presented in this thesis, suggest that autistic individuals are less reliant on expectations of upcoming stimuli during perception than non-autistic individuals.

Finally, the results from the psychometric studies presented in this thesis are also in line with the suggestions of an imbalance between prior expectations and sensory information in autism. The relationship between intolerance of uncertainty, sensory information and autism that was reported in chapter 10 extended the findings of Neil et al. (2016) to an adult sample. As discussed above, it is impossible to infer the direction of causality within this relationship and so the results do not shed any further light on whether attenuated priors (Pellicano and Burr, 2012b) or increased sensory precision (Brock, 2012; Lawson et al., 2014) underlie the

perceptual differences found in autism. However, the results support the uses of Bayesian approaches in explaining perceptual inference and perceptual atypicalities in autism. These findings also show that behavioural and clinical features, relating to levels of anxiety and attitudes towards uncertainty, are associated with sensory processing which supports the numerous claims that perceptual processing differences might underlie a wide range of the features associated with autism (Lawson et al., 2014; Pellicano, 2013; van Boxtel and Lu, 2013; Van de Cruys et al., 2014).

11.4 Limitations

When discussing the findings of this thesis, it is important to take the limitations of the different studies into consideration in order to both evaluate the strength of the evidence presented here and to highlight approaches that could be taken in future studies to overcome such limitations. A number of limitations that were specific to each of the different experiments presented in this thesis have been discussed within their respective chapters. As these have already been highlighted, they will not be discussed again here. Instead, a more general assessment of limitations across the thesis will be presented.

One important limitation of this thesis as a whole is the lack of a link between the two different levels at which differences in autism were assessed. Both behavioural and psychometric studies were included, but there was little overlap between these approaches and so deeper inferences could not be drawn as to how the behavioural effects reported here might relate to the psychometric measures. This is certainly an important area to focus on in future research and potential ways in which studies can bridge this gap will be discussed in the next section.

While sex differences were considered within the psychometric studies, this was primarily done to check for potential confounding effects when testing for group differences between the autistic and non-autistic participants. A deeper investigation of potential sex effects, and how these could influence the associations found between intolerance of uncertainty, anxiety and sensory issues, was not considered in these studies. Similarly, sex differences were not evaluated across the behavioural studies either, primarily due to the sample sizes not allowing for it.

Sex has been found to influence a number of aspects of behaviour in autism and males have a higher chance of being diagnosed with an autism spectrum condition (Lai et al., 2015). While there are no direct reports of sex differences in attitudes towards uncertainty, males and females have been shown to process and react to task-based errors in different ways (Fischer et al., 2016). Neural responses to unexpected information have also been shown to

be influenced by sex (Brumback et al., 2012). Future studies should focus on including larger samples that allow for potential effects of sex to be considered.

Another key limitation of the studies presented here concerns the selectivity of the samples included in this thesis. The autism groups recruited for the different behavioural tasks only included high-functioning individuals[1]. Individuals that are referred to as low-functioning are thought to make up approximately a third of all autistic individuals and are therefore an important group in terms of furthering our understanding the condition (Chakrabarti, 2017). Inclusion of such groups is often reliant on behaviour paradigms that avoid overly complex instructions or by using passive neuroimaging approaches (Jack and A. Pelphrey, 2017). By only including high-functioning individuals, the studies presented here overlooked a proportion of the heterogeneity within the autistic population.

Finally, while not necessarily a limitation *per se*, it is important to acknowledge that the studies presented in this thesis only inform certain areas of our understanding of autism. Specifically, the experiments included in this thesis were designed to explore questions at the behavioural and psychometric levels. These give us insights into how autistic individuals respond behaviourally to different situations in which prior information can be utilised to aid perception. However, these studies are limited in the extent to which they inform us about the neurocomputational processes that drive the observed differences. Potential ways of assessing the potential neural mechanisms that drive the behavioural results found in this thesis will again be discussed in the following section.

11.5 Future directions

The studies presented in this thesis aimed to answer a number of questions regarding the behavioural aspects of how visual perception is influence by predictive information in autistic individuals as well as the extent to which autistic individuals' attitudes towards uncertainty may be linked to clinical symptoms. There are still a number of outstanding questions in this area and I plan to carry out further studies to expand and build on the findings presented here. A brief outline of the areas and approaches that will be taken in these future studies will be discussed below.

[1] While I am aware that there are some issues surrounding the use of the terms *high-* and *low-functioning*, I have included them here as they are the conventional terms used to described differences in cognitive abilities in autism (Bennett et al., 2018; Laurelut et al., 2016; Mallett and Runswick-Cole, 2012). When using the terms low- and high-functioning, I am differentiating between individuals who have minimal verbal ability and/or intellectual difficulties and those who don't. However, it is worth briefly noting that the term high-functioning autism may be considered to disregard some of the challenges faced by individuals affected by the condition that are not always apparent (Hull et al., 2017; Lai et al., 2016; Livingston and Happé, 2017).

11.5.1 Extension of behavioural assessment

There are a number of potential research directions which future studies can take to build on the work presented in this thesis. Replication of results is of vital importance, particularly due to reports of low-levels of replicability in the cognitive sciences (Open Science Collaboration, 2015) and so one priority for future studies should be assessing whether the results presented in this thesis replicate. With any experimental study, there are always ways in which the experimental work can be extended and built on to explore additional hypotheses. Throughout the thesis, I highlighted a number of ways in which each of the individual studies could be extended in future research. As these specifics have already been discussed, I will instead focus on a broader consideration of future approaches to behavioural studies in this area.

As mentioned during the discussion of the limitations of this thesis, the results reported here did not include a direct link between behavioural performances and attitudes towards uncertainty. As robust group differences have been found in self-report measures of intolerance of uncertainty (Boulter et al., 2014; Chamberlain et al., 2013; Neil et al., 2016), a key area to focus on in future studies is gaining a better understanding of how variation in intolerance of uncertainty relates to behavioural aspects of the ways in which individuals utilise prior expectations during perception and cognition. One study which looked at the link between behavioural performances and intolerance of uncertainty considered whether behaviour in the *Beads Task*, a behavioural measure of data gathering in decision-making (Ross et al., 2015), was associated with scores on the IUS in individuals with anxiety disorders (Jacoby et al., 2014). The Beads Task has previously been used to find differences in cognitive strategies between autistic and non-autistic individuals (Brosnan et al., 2014) as well as linking performance on the task to differences in empathising and systemising (Brosnan et al., 2013). Jacoby et al. (2014) found that intolerance of uncertainty was correlated to both decision-making behaviours and higher reported levels of distress during the task, showing that variation in scores on the IUS can be predictive of task-based performance. While this example uses a decision-making task rather than a perceptual task, a similar approach could be used with other types of behavioural task including those presented within this thesis.

Another point that was briefly highlighted in the limitations section was the lack of neural-level insights provided by the studies in this thesis. One way in which stronger inferences can be made about possible neural mechanisms involved in the observed behavioural differences is by applying computational modelling to behavioural data (Churchland et al., 2016; Friston et al., 2014; Heeger et al., 2017; Stephan and Mathys, 2014). Such approaches can be seen across a number of publications which model prediction errors across different hierarchical levels (Diaconescu et al., 2017b; Marshall et al., 2016; Sevgi et al., 2016) and, in particular,

the study from Lawson et al. (2017) which applied these approaches to behavioural data from an autistic sample.

There is scope for such approaches to be applied to some of the data collected here, in particular the results from chapter 6. Following the claims by Van de Cruys et al. (2014), that newer information will be given overly-high weight in autistic individuals, the influence of variations in task uncertainty on reaction times could be assessed to probe for differences in the relative weight given to older and newer information in autistic individuals (see Bröker et al. (2018) and Zhang and Rowe (2015) for methods that approach similar questions). By adopting more sophisticated methods of analysing the data, future studies could shed light on the underlying mechanisms involved in the behavioural differences observed in this thesis.

11.5.2 Electrophysiology

While one way of examining the underlying neurocomputational mechanisms involved in such processes is through computational modelling of behavioural data, similar questions can also be assessed through neuroimaging techniques. Functional MRI (fMRI) has been a popular method for understanding patterns of activity in the brain and boasts strong spatial resolutions as well as the advantage to assess deeper brain regions. However, fMRI is limited by poor temporal resolution (Kim et al., 1997) which results from the nature of the hemodynamic response (Glover, 2011). While EEG based approaches are limited to cortical areas and have lower spatial resolution, their increased temporal resolution makes them suitable for measuring hierarchical signaling in the brain (Diaconescu et al., 2017a; Stefanics et al., 2018).

For example, mismatch negativity (MMN) signals can be used as a measure of the activation within brain networks that process deviance detection and build perceptual predictions (Wacongne et al., 2012). These signals can be evoked by visual stimuli (Kremláček et al., 2016) and are thought to be sensitive to implicit temporal predictions during visual perception (Kimura, 2012). This suggests that measuring MMN signals would be a very suitable approach for detecting neural signatures that would be relevant to the behavioural tasks in this thesis. This signal is thought to represent cortical predictive processes (Stefanics et al., 2018) and is therefore a useful tool for evaluating possible neurocomputational mechanisms involved in perceptual inference, such as predictive coding (Garrido et al., 2009).

EEG based studies would allow for expectation effects to be assessed independently of behaviour, which overcomes any potential issues with concerns that other aspects of behaviour might mask potential differences in autistic individuals. Previous research looking at the acquisition and use of predictive information has reported distinct patterns of neural activity in autistic individuals despite an absence of behavioural differences (Zwart et al., 2018a).

Using electrophysiological methods would increase the chances of detecting differences in how individuals process predictive information that may not be apparent at a behavioural level. Another additional advantage with such approaches is that they would also allow for a wider range of participants to be involved in research, such as nonverbal adults or young infants. This would overcome one of the main limitations of this thesis, by better capturing the full heterogeneity of the autism spectrum.

Combining psychometric, behavioural and electrophysiological approaches would allow for a deeper understanding of how autistic individuals use predictive information to facilitate perception. Simultaneously testing for individual differences at these 3 levels will allow for the relationships between these distinct levels to be understood. Specifically, this will help to clarify how variation in computational processes within the brain affect the way in which predictive information is dealt with under different levels of uncertainty and, in turn, how this extends to differences in an individual's attitudes towards uncertainty as well as broader aspects of personality and, in the case of autism, clinical difficulties such as anxiety.

11.5.3 Participant involvement

When moving forward with my research and building upon the work presented in this thesis, I plan to adopt an approach that informs the design and implementation of future studies through patient and public involvement (PPI). This will involve carrying out a number of group-based sessions to get feedback from stake-holders within the autistic community on the work I have presented here. This will give me the opportunity to find areas that these stake-holders feel would be important for future research. Such approaches to research are not simply based on ethical motivations for involving community members in research (Domecq et al., 2014) but also the fact that such processes have been found to have a positive impact on the quality and impactfulness of the research they produce (Pellicano et al., 2014b).

This approach has been used in various different research areas, including autism. A number of reports have highlighted the importance of involving autistic individuals in the research process (Fletcher-Watson et al., 2018; Pellicano et al., 2014a). There are several benefits to such approaches which are becoming an increasingly popular method of informing research priorities and reducing inefficient or wasteful uses of research funding (Chalmers et al., 2014). Care needs to be taken to avoid what is referred to as 'token' or 'selective' PPI, where the individual or group overseeing the PPI focuses only on input that is in line with their own views or aims and disregards conflicting suggestions (Russell et al., 2018).

Involving members of the autistic community in research is one way of helping to use scientific research to facilitate the provision of services to support autistic individuals (Pellicano et al., 2014a). This not only helps to guide the focus of research towards areas

that are relevant and likely to have an impact on the lives of autistic individuals but can also improve the engagement and reach of research (Frazier et al., 2018). There have been previous reports of dissatisfaction within the autism community with regards to the focus and outputs of research. This makes a strong case for increasing the involvement of autistic people in research and improving efforts to connect researchers with the relevant communities. These approaches are invaluable in informing how researchers can translate scientific findings into useful practices (Fletcher-Watson et al., 2018).

Such approaches should also focus on understanding what the community regard as meaningful outcomes for research (Bal et al., 2018). Previous work focusing on the interests of the autistic community have reported a call for increasing the focus of research on making differences on a day-to-day basis (Pellicano et al., 2014b) and improving quality of life in autistic individuals (Haker et al., 2016). This can be achieved by understanding what factors attribute to quality of life in autistic individuals and focusing on ways to enhance these factors (Mason et al., 2018; McConachie et al., 2018), such as self-worth and employment (Lorenz et al., 2016). These groups will help me to guide my future research towards areas that will have higher value to those it will impact.

To facilitate the planned PPI groups and improve the wider impact of the findings of this thesis, I plan to follow up the material presented in this thesis by producing a series of 'easy read' documents that communicate the findings of this thesis for a non-expert audience. These will help to summarise the current findings for those involved in the PPI groups as well as providing a resource which is more accessible to those without a scientific background. When Pellicano et al. (2013) published the *A Future Made Together* report, which reviewed the state of autistic research in the UK, they also released an 'easy read' version of their report designed to be accessible to the general population.

Clarity and readability are important when communicating scientific findings, particularly when the intended audience consists of non-specialists (Gernsbacher, 2018; Yeung et al., 2018). When involving community members in research, it is vital to adopt a common vocabulary that doesn't exclude those without a scientific background (Long et al., 2017). While being mindful of the language used, it is also imperative that such approaches avoid the potential pitfall of being overly patronising (Milton et al., 2012). Indeed, autistic individuals tend to have greater scientific understanding of the condition than the general population (Gillespie-Lynch et al., 2017).

Aside from supporting the PPI groups, these 'easy read' documents will also provide a way of communicating the results of this thesis to those outside of academia and avoids issues with inaccessibility that increasingly affect scientific publications (Plavén-Sigray et al., 2017). Improving the accessibility of scientific writing can increase its impact with a wider

audience (Freeling et al., 2019) and efforts to move away from a purely 'science for scientists' approach to scientific reporting are gaining popularity (Doubleday and Connell, 2018).

11.6 Conclusion

Autism is an incredibly complex and interesting condition, that manifests in a wide variety of ways. A unique aspect of autism is the fact that certain abilities are intact or enhanced despite difficulties in other areas. One of the appealing aspects of using Bayesian models of perception to understand and theorise about specific differences in autistic individuals is it allows for autism to be framed as a divergence of behaviours rather than a disability. While this is true of other accounts as well, the Bayesian framework has strong explanatory power across the different features of autism.

The studies presented in this thesis provide a thorough empirical investigation of a number of different hypotheses related to explanations of autism within the Bayesian framework. Overall, the results presented here show support for the suggestions that the relative influence of prior expectations is attenuated in autism. The role of prior expectations during perception is a complex process and further research should focus on building upon the growing body of work in this area in order to help establish a clearer picture of how these mechanisms are linked to autism.

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Appendix A

Additional outputs

	sum_sq	df	F	PR(>F)	eta_sq	omega_sq
Group	0.008910	1.0	0.703712	0.403920	0.008272	-0.003442
Response type	0.003564	1.0	0.281455	0.597149	0.003308	-0.008348
Group*Response type	0.001108	1.0	0.087479	0.768137	0.001028	-0.010602
Residual	1.063564	84.0	NaN	NaN	NaN	NaN

Table A.1 Analysis from the interrupted search task. Full results from the 2-way ANOVA with log probability ratio as the dependent variable, 'Group' (autism or control) as the between-subject measure and 'Response type' (rapid or slow) as the within-subject measure.

	sum_sq	df	F	PR(>F)	eta_sq	omega_sq
Group	0.015905	1.0	1.684142	0.197927	0.019068	0.007659
Condition	0.024223	1.0	2.564813	0.113020	0.029039	0.017519
Group*Condition	0.000701	1.0	0.074183	0.786009	0.000840	-0.010365
Residual	0.793317	84.0	NaN	NaN	NaN	NaN

Table A.2 Analysis from the interrupted search task. Full results from the 2-way ANOVA with absolute log probability ratios as the dependent variable, 'Group' (autism or control) as the between-subject measure and 'Condition' (low or high) as the within-subject measure.

	Sum of Squares	df	Mean Square	F	p
Position	0.068	2	0.034	5.776	0.004
Position * Group	0.042	2	0.021	3.549	0.032
Residual	0.673	114	0.006		
Session	0.085	1	0.085	11.133	0.001
Session * Group	0.017	1	0.017	2.291	0.136
Residual	0.433	57	0.008		
Position * Session	0.005	2	0.003	0.448	0.640
Position * Session * Group	0.002	2	8.274e-4	0.140	0.870
Residual	0.675	114	0.006		

Table A.3 Analysis from the serial reaction time task. Within-subject effects for the main ANOVA on expectation effect.

	Sum of Squares	df	Mean Square	F	p
Group	0.054	1	0.054	4.766	0.033
Residual	0.640	57	0.011		

Table A.4 Analysis from the serial reaction time task. Between-subjects effects for the main ANOVA on expectation effect.

		Mean Difference	SE	t	p_{bonf}
Start	Middle	-0.019	0.010	-1.869	0.200
	End	-0.036	0.010	-3.579	0.002
Middle	End	-0.018	0.011	-1.687	0.291

Table A.5 Analysis from the serial reaction time task. Post Hoc comparisons between the different positions (start, middle and end) across the task for all participants.

	Sum of Squares	df	Mean Square	F	p
Position	0.118	2	0.059	7.058	0.002
Residual	0.519	62	0.008		
Session	0.014	1	0.014	1.656	0.208
Residual	0.258	31	0.008		
Position * Session	0.006	2	0.003	0.438	0.647
Residual	0.436	62	0.007		

Table A.6 Analysis from the serial reaction time task. Within-subject effects for the control-only ANOVA on expectation effect.

	Sum of Squares	df	Mean Square	F	p
Position	0.002	2	8.308e-4	0.282	0.755
Residual	0.153	52	0.003		
Session	0.082	1	0.082	12.251	0.002
Residual	0.175	26	0.007		
Position * Session	0.001	2	6.115e-4	0.133	0.876
Residual	0.240	52	0.005		

Table A.7 Analysis from the serial reaction time task. Within-subject effects for the autism-only ANOVA on expectation effect.

		Mean Difference	SE	t	p_{bonf}
Start	Middle	-0.029	0.015	-1.906	0.198
	End	-0.061	0.015	-4.004	0.001
Middle	End	-0.031	0.018	-1.763	0.263

Table A.8 Analysis from the serial reaction time task. Post Hoc comparisons between the different positions (start, middle and end) across the task for the control group only.

Cases	Sum of Squares	df	Mean Square	F	p
Group	0.129	1	0.129	6.148	0.015
Condition	0.981	2	0.490	23.426	$< .001$
Group * Condition	0.017	2	0.009	0.413	0.663
Residual	2.469	118	0.021		

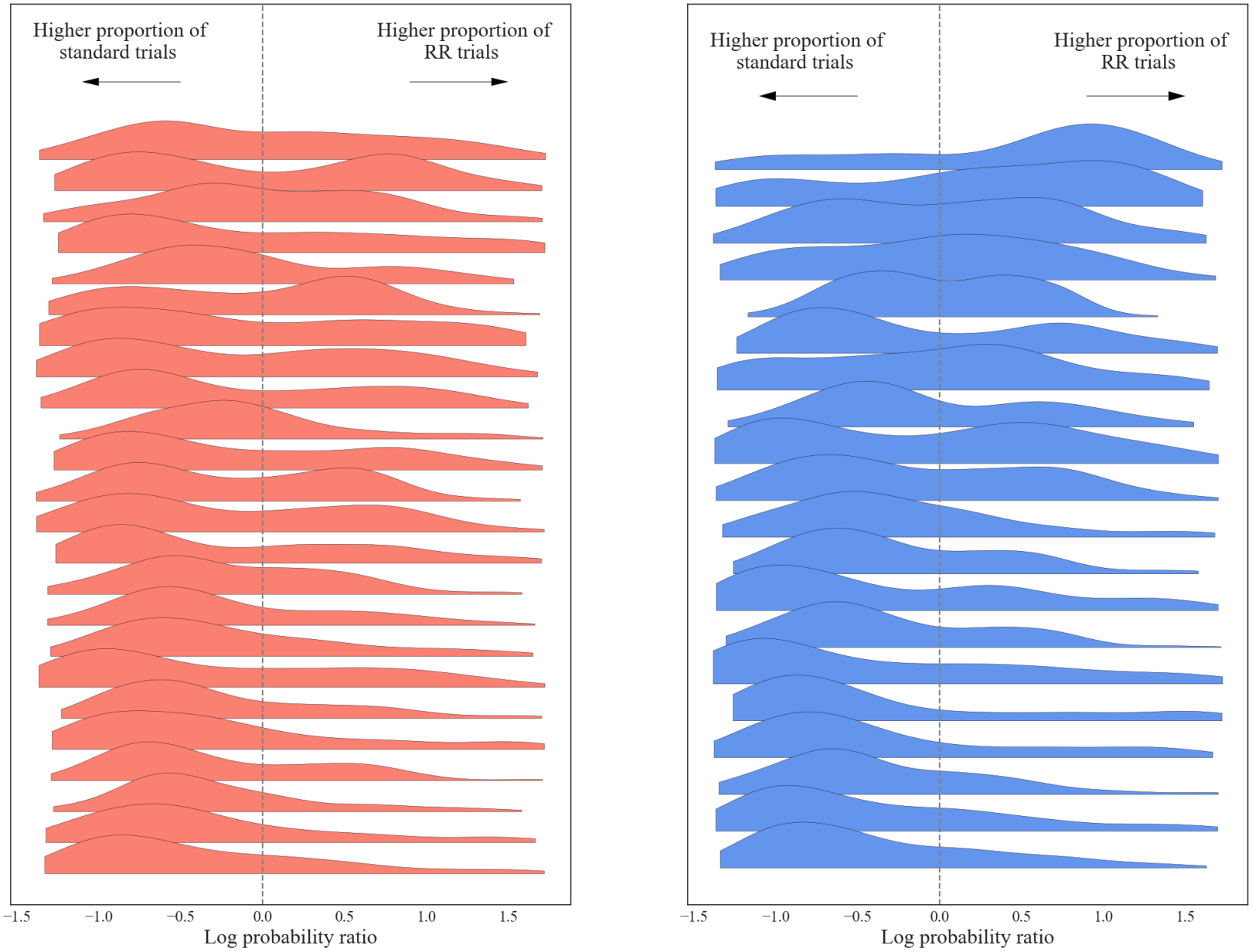
Table A.9 Analysis from the categorical statistical learning task. Full results from the 2-way ANOVA with the proportion of correct responses as the dependent variable and both 'Group' (autism or control) and 'Condition' (standard, category or generalisation) as between-subject measures.

		Mean Difference	SE	t	Cohen's d	p_{bonf}
Standard	Category	0.188	0.032	5.892	1.303	$< .001$
	Generalisation	0.192	0.032	6.009	1.170	$< .001$
Category	Generalisation	0.004	0.032	0.114	0.028	1.000

Table A.10 Analysis from the categorical statistical learning task. Post Hoc comparisons of performance across condition types in the recall phase.

Appendix B

Supplementary figures



(a) CTR participants.

(b) ASC participants.

Fig. B.1 Distributions of log probability ratio scores for all participants in the interrupted search task. Distributions are ordered from highest mean l.p.r (top) to lowest mean l.p.r (bottom) and shown separately for (a) CTR and (b) ASC participants.

(a) Airport.

(b) Bathroom.

(c) Bedroom.

(d) Bridge.

(e) Coast.

(f) Field.

(g) Forest.

(h) Kitchen.

(i) Mountains.

(j) Pool.

(k) Road.

(l) Sky scraper.

Fig. B.2 Example images for the 12 different category types used in the categorical statistical learning task.